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Three Empirical Essays on Energy and Labor Economics

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ABSTRACT

This dissertation analyzes the differences between private and non-private firms in two contexts. Chapters 1 and 2 examine the electricity industry in the United States and the motivation behind electric utilities' usage of demand side management programs. The first chapter focuses on load management programs, which decrease electricity demand during the peak hours of the day. It looks into the impact of a plausibly exogenous decrease in natural gas prices on the utilization and capacity of these programs. The second chapter analyzes the relationship between electricity market deregulation and electric utilities' energy efficiency activity. The third chapter investigates the impact of Chinese enterprise restructuring on employment, wage bills, and productivity. All three chapters show that different objectives due to ownership type lead to differences in firm behavior.

THREE EMPIRICAL ESSAYS ON ENERGY AND LABOR ECONOMICS

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1. Three Empirical Essays on Energy and Labor Economics

This dissertation examines the differential impact of ownership type on firm decisions, specifically comparing private and non-private firms. The first two chapters analyze how private and non-private utilities in the United States differ on their usage of electricity conservation programs, also known as demand side management (DSM) programs. These chapters examine the motivation behind the usage of DSM programs and the roles of cost minimization and regulatory pressure. The third chapter of this dissertation investigates firms that transition from state-owned to privately-owned in China from 1998 through 2006. It looks at the impact of restructuring on labor market outcomes, including employment, wage bills, and labor productivity.

To explain in more detail, the first chapter examines the impact of a decline in natural gas prices on the usage and capacity of electric utilities' load management programs (which decrease usage of electricity during peak hours of the day). On a day when electricity demand is high, utilities can choose to increase their supply of electricity by running an additional gas power plant or they can opt to decrease the demand of electricity by employing a load management program. Due to the role of natural gas plants and load management programs in meeting peak demand, the two can be seen as substitutes. Using a change in natural gas prices due to advancements in mining technology, a difference-in-differences methodology is employed to determine the motivation behind why utilities use and maintain load management programs. These programs are costly to run and one hypothesis is that these programs are used when they are the more cost effective method of meeting peak demand. An alternative hypothesis is that utilities are under regulatory pressure to use and maintain these programs. The results indicate that following a decline in natural gas prices, non-private utilities that generate their own electricity will decrease the usage of their load management programs by approximately 2 percent of peak summer demand. Load management program size is estimated to decline by 5 percent of peak demand for non-private utilities when gas prices fall. These results are consistent with the hypothesis of cost minimization and provide some empirical evidence that gas generation and load management programs are substitutes for meeting peak demand. For private utilities, the results are not statistically significant.

The second chapter analyzes electricity market deregulation and its impact on utilities' energy efficiency activity (which decreases energy usage during all hours of the day). This chapter seeks to determine the motivation behind electric utilities' energy efficiency activity, specifically analyzing the role of regulatory pressure. During the late 1990s and early 2000s, several states deregulated their electricity markets. The push for a change in market structure was due to pressure to increase competition in order to decrease electricity prices. This paper uses the change in the regulatory environment, which occurred in some states but not others, to analyze the impact of deregulation on electric utilities' energy efficiency activity. The results indicate that following a change in market structure, private utilities decreased their energy efficiency activity by approximately 200,000 MWh per utility, an amount of electricity that is roughly equivalent to a natural gas plant running at full capacity for a year.

The third and final chapter of this dissertation explores labor market outcomes in China for state-owned enterprises that transitioned to privately-owned from 1998 through 2006. In the mid-1990s, the Chinese government introduced a policy intended to privatize small and medium-sized state-owned enterprises while retaining ownership of larger state-owned firms. Using a

propensity score matching difference-in-differences methodology to address the issue of selection bias, employment, wage bills, and productivity are examined before and after restructuring occurred. The results show that firms that transition from state-owned to privately-owned decrease their employment on-average by approximately 7 percent, reduce total real wages by 7 to 10 percent on-average, and increase labor productivity (measured as sales per worker) by 11 to 26 percent on-average following a change in ownership structure. The employment and wage effects fade over time, while the productivity effects persist for a longer period of time.

2. The Impact of Natural Gas Prices on Utilities' Load Management Program Usage and Capacity

2.1 Introduction

In recent decades, following the deregulation of electricity markets, the California Electricity Crisis, and the development of more sophisticated technology, many residential customers and those in the electricity industry have been advocating for different ways to lower electricity prices and promote energy conservation. The push for discovering ways to manage electricity efficiently has continued to grow recently due to concerns about climate change. In 2012, the electricity sector was responsible for 32 percent of greenhouse gas (GHG) emissions in the United States, making it the largest source of GHG emissions in the U.S.[1] It was also the single largest source of carbon dioxide (CO_2) emissions in the U.S., contributing 38 percent of the nation's total CO_2 emissions.[2]

In an attempt to solve the problem of increased electricity demand and in turn greater fossil fuel combustion, some policymakers have focused on the supply side of the equation and tried to promote clean energy and renewable forms of energy generation. Developing technologies have led to an increase in solar, wind, and other renewable sources of energy as well as a shift away from traditional fossil fuels such as coal. Furthermore, around 237 gigawatts (GW) of natural gas generation capacity was added between 2001 and 2010 to keep up with the growing demand for electricity.[3] This made up over 80 percent of capacity added during that time period. Of the 237 GW of new capacity, 75 GW were new combustion turbine plants, which are primarily used during the peak hours of the day, while the remaining units consisted of

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[1] http://www.epa.gov/climatechange/ghgemissions/sources/electricity.html
[2] http://www.epa.gov/climatechange/ghgemissions/gases/co2.html
[3] http://www.eia.gov/todayinenergy/detail.cfm?id=2070

combined-cycle units, steam turbine plants, and other natural gas plants.[4] Natural gas plants are particularly attractive for meeting growing demand because they produce fewer emissions than coal plants, have low construction times and low capital costs, and are relatively faster at starting and ramping up.[5] At the same time, other policymakers have thought about solving the problem from the demand side of the equation. Programs that focus on conservation from the demand side are broadly termed *demand side management (DSM) programs*. One type of DSM program that is used during peak hours of the day is a *load management (LM) program*. This paper looks at the substitutability of natural gas generation and LM programs in meeting peak demand and analyzes the motivation behind the usage and size of LM programs.

Many demand side management programs in the United States started in response to the energy crises in 1973 and 1979. While these programs have been in place for a few decades, there has been renewed interest in these types of programs following electricity market deregulation and the increase in energy prices across the country during the last decade. DSM programs have been used in the industrial sector, but the recent push has been for implementation at the residential customer level. DSM programs encompass both *load management (LM)* and *energy efficiency (EE)* activity. Generally, load management refers to activities to curb energy consumption during the peak hours of the day or during high price periods. Load management programs are sometimes referred to as demand response (DR) programs. Customers who voluntarily decrease their demand for electricity during peak hours of the day are paid a dollar amount (usually per MW) by the utility or are compensated with a lower electricity rate. Using data from the New York Independent System Operator (NYISO), Figure 2.1 illustrates an hourly load curve for a summer day with and without a hypothetical load

[4] http://www.eia.gov/todayinenergy/detail.cfm?id=2070
[5] http://www.eia.gov/todayinenergy/detail.cfm?id=2070

management program. The NYISO operates New York State's electricity grid and manages the competitive wholesale electricity markets in the state.[6] It collects hourly load data for all the electric zones in the state, as well as other information about market operation. With a LM program, electricity demand is reduced during the peak hours of the day and increased during off-peak hours. This is why some refer to load management programs as *load shifting programs*. The hypothetical load management program in Figure 2.1 reduces peak demand by 1,000 MW and increases demand in the off-peak hours by 1,000 MW. Energy efficiency (EE), on the other hand, refers to efforts to reduce the amount of energy required to do certain activities and typically involves energy conservation across all hours of the day, not only during peak periods. While EE programs play an important role in energy conservation, the main focus of this paper is load management programs.

Over the course of a day, there are variations in the price of electricity due to a number of different factors, including the weather and emergency outages of power plants or transmission lines. In extreme cases, the electricity price in certain areas can exceed several hundred dollars per megawatt hour (MWh), causing spikes in the price. Utilities cannot immediately pass on the cost to their customers, although they may adjust their tariff rates each quarter or year to account for the increasing price of electricity. Load management programs can help solve the problem of high electricity demand and prices during peak periods as customers shift their demand from the peak period to an off-peak period. An additional benefit of shifting load from peak periods to off-peak periods is the use of cleaner and more efficient power plants. For example, due to wind patterns, wind plants generate more electricity at night than during the day. So, if demand is shifted to off-peak hours, it can be met by wind plants rather than by running coal plants to generate the electricity demanded during peak hours.

[6] For more information on the NYISO, see http://www.nyiso.com/public/index.jsp

Load management programs lower the peak demand for energy, reducing the need to construct new, expensive generation units. Therefore, a long-run benefit of using and maintaining a LM program is the avoided cost of siting new generation, which can be quite high. In the short-run, without load management programs, utilities would have to run their existing, more expensive units more often in order to meet the demand during peak hours. Utilities are adding load management programs to their portfolio and pairing them with generation facilities to meet peak demand needs.

This paper examines elements that have impacted the usage and capacity of load management programs in the United States during the last ten years. It specifically focuses on electric utilities' motivation behind using and maintaining these programs. Utilities could be using these programs due to pressure from regulatory agencies or because they are the most cost effective option. Not every utility has a load management program, and those that have a program vary both in the size of their programs and in their program utilization. Using empirical evidence, this analysis focuses on utilities that have load management programs and analyze whether the motivation behind LM program usage and size is cost minimization via the substitution between the utilization of natural gas plants and LM programs during the peak hours of the day. To examine this, an exogenous decrease in natural gas prices during the late 2000s is exploited and a difference-in-differences estimation technique is employed.

The findings imply that there is substitutability between gas generation and both the usage and capacity of load management programs for non-private utilities. Following a gas price decrease, the results imply that non-private utilities with generation will decrease their usage of the load management programs by 1.51 percent to 1.95 percent of their peak summer demand. Using program capacity as the dependent variable yields similar results – non-private utilities with generation decrease the size of their programs by 4.49 percent to 5.18 percent of their peak summer demand. These results are statistically significant and support the hypothesis that utilities will use their load management programs less when an alternative becomes cheaper.

For private utilities, the results are positive but not statistically significant for program usage and program capacity. This does not mean that private utilities are not motivated by cost minimization. However, the results suggest that other factors, such as regulatory pressure, may overwhelm the impact of cost minimization for these utilities.

The paper proceeds as follows. The next section explains how supply and demand interact in the electricity market, defines several key terms related to LM programs, discusses the state of existing programs in the United States, and describes the relationship between natural gas generation and LM programs. After that, the previous literature related to LM programs is summarized. Then the theory behind a utility's decision to choose to run a natural gas plant or to employ a LM program during the hours of peak demand is explained. Included is a simple model of the utility's cost minimization decision. The section following that describes the data used. Then the methodology for answering the research questions is explained, various regression specifications are described, and the results are presented. Finally, some conclusions and policy implications from this research are offered.

2.2 Background

2.2.1 Supply and Demand of Electricity

Electricity is a unique commodity because it is an inelastically demanded good that cannot be stored at grid scale. The production of electricity can sometimes be subject to short-term capacity constraints because certain types of power plants take a longer amount of time to start up. The demand for electricity is highly variable and as a result, there are time periods when there is plenty of capacity available and the incremental costs only consist of fuel costs or operating and maintenance (O&M) costs. On the other hand, during periods of high demand, as capacity gets tighter, higher cost units must be run, leading to sharp increases in the wholesale price of electricity. As a result of increased demand, utilities are forced to use higher cost plants to meet their electricity demand.

In order to prevent blackouts from occurring, the supply and demand of electricity must be balanced in real time. To ensure that there is enough supply to meet demand, the North American Electric Reliability Corporation (NERC) sets a target reserve margin for each region of the country. The reserve margin is defined as "the amount of unused capacity at the time of peak load, expressed as a percentage of expected peak demand".[7] For the summer 2014, the target reserve margins ranged from 15 percent in Texas to 38 percent in the Southwest Power Pool. Demand side management programs can help reduce the expected peak demand in an area, and thus ensure that the reserve margin is at a safe level. Load management programs also play a role in preventing blackouts and lengthy power outages due to excess demand. Programs that are only used during emergency situations, such as when there is a sudden, unplanned generation outage, can be referred to as *reliability-driven programs*. As DSM programs continue to grow, they play an increasingly important role in helping to maintain the balance between supply and demand.

The constant changes in the supply and demand for electricity lead to different market clearing wholesale electricity prices every half-hour or hour. The price faced by the customer also varies based on customer type. There are different classifications of customers including residential, industrial, and commercial. Industrial and commercial customers are more likely to

[7] More information on reserve margins can be found at http://www.eia.gov/todayinenergy/detail.cfm?id=16791

be subject to time-of-use pricing, which passes on the cost for each hour of electricity generation and reflects more of the volatility in the electricity price. However, the price that is passed onto the residential customer is the retail price, which in most parts of the United States is relatively flat with adjustments made only a few times a year. Residential customers are subject to the highest average retail price. In 2013, the average retail electricity price was 12.12 cents per kilowatt hour (kWh) while the prices for commercial and industrial customers were 10.29 and 6.82 cents per kWh, respectively.[8] Additionally, residential customers bring in the largest amount of revenue from retail sales of electricity.[9] Several programs, including demand side management programs, have aimed to make the economic incentives of customers more accurately reflect the time-varying wholesale cost of electricity. The sharp increases in prices could be dampened by price-responsive demand.

2.2.2 Current Load Management Programs

Although the broad category of load management programs exists throughout the country, the details of each program vary based on each specific utility and other factors, such as state regulations. While LM programs are increasing in popularity, there is potential for further expansion, which could lead to additional reductions in peak demand and savings for utilities since they are not paying peak prices for electricity. Utilities can either grow the existing programs or create new LM programs to expand the reach of these services. As of 2010, existing DR programs in the U.S. have the capacity to offset 4 percent of U.S. peak demand.[10] As a reference point, the 2010 non-coincident summer peak demand – "non-coincident" meaning that the peak demands in each region do not have to occur at the same time – for the continental U.S.

[8] Average electricity price data by sector are from the Electric Power Monthly, Table 5.3, which was released on March 21, 2014 and can be found at: http://www.eia.gov/electricity/data.cfm
[9] Electricity Power Monthly, Table 5.2, released on March 21, 2014; http://www.eia.gov/electricity/data.cfm
[10] National Action Plan on Demand Response, p. 5

was 767,948 MW.[11] Using this value for peak demand, it translates into a savings of 30,718 MW. This represents the generating capacity of roughly 30 nuclear power plants.

The existing DR programs in the United States have been in place for several decades and are mostly reliability-driven programs. As with electricity consumption throughout the country, there are significant geographical variations in the amount of existing demand response activity. There are a number of different types of LM programs around the U.S. and their regulations vary at the state level. California, Florida, and New England are areas with a significant amount of DR activity, while Alaska, Montana, and Wyoming have a low amount of activity.

2.2.3 Relationship between Natural Gas Generation and Load Management Programs

When utilities and independent system operators (ISOs) decide which power plants to run first to generate electricity, they use the plants with the lowest variable operating cost first. The order in which the plants are used can be referred to as an *electricity supply curve* or a *dispatch curve*. Baseload plants such as coal and nuclear plants are typically first used. These are power plants that tend to be cheaper to run, have lower variable costs, and take a longer time to start up and ramp down. Baseload plants usually run the full 24 hours every day with downtime only when there are maintenance outages. Natural gas plants are towards the end of the generation queue because their marginal costs are higher than the baseload plants; so they are usually run last.[12] Information on capacity factors for different types of power plants is available from the U.S. Energy Information Administration (EIA). Capacity factors measure how much electricity is generated relative to the amount the plant can produce based on its maximum capacity if it was

[11] Information on historical U.S. demand broken down by region and for the country as a whole can be found at: http://www.eia.gov/totalenergy/data/annual/showtext.cfm?t=ptb0812a
[12] For an example of a hypothetical electric generator dispatch curve based on variable operating cost, see http://www.eia.gov/todayinenergy/detail.cfm?id=7590

fully operational during the same amount of time.[13] The data indicate that average utilization of natural gas capacity increased from 2005 to 2010. However, for a combined cycle natural gas plant, average utilization during peak periods is still only about 50 percent, and during off-peak periods the number drops to about 30 percent.[14] A combined cycle unit consists of both a combustion turbine and a steam turbine. It takes the waste energy produced by the combustion turbine and uses it as an input into a steam boiler. This is then used by the steam turbine to produce additional electricity, resulting in an efficiency increase in the unit as a whole.[15] Natural gas combustion turbines (NGCTs), which are typically used as peaking units, have an even lower capacity factor. Their annual capacity factor has been around 5 percent for the time period from 2008 to 2013.[16] Using data from the EIA, Figure 2.2 displays the monthly capacity factors for NGCT generators from January 2012 through December 2013. Looking more closely at the monthly capacity factors shows that NGCTs are being utilized more often in the hot summer months, which supports their hypothesized usage as peaking units. As a reference point and for comparison purposes, using 2010 data, the Vogtle nuclear power plant, a large baseline plant in Georgia, has a capacity factor of 95 percent for the year.[17]

If there is a day when the electricity demand is high and approaches the amount of electricity supply available and online, a utility could have several options for meeting the additional demand. One option is running a natural gas plant. Another option for utilities to meet the increased demand is to ask their customers who are participants in a LM program to reduce their load for an hour (or until the electricity demand is met and starts to decrease). Due

[13] Additional information about capacity factors can be found on the EIA website, http://www.eia.gov/tools/faqs/faq.cfm?id=187&t=3
[14] http://www.eia.gov/todayinenergy/detail.cfm?id=1730
[15] http://www.eia.gov/tools/glossary/?id=electricity
[16] http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_6_07_a
[17] http://www.eia.gov/todayinenergy/detail.cfm?id=1710

to their roles in meeting peak demand, these two options can be viewed as substitutes. Running a gas plant increases the supply of electricity while encouraging customers to decrease their loads decreases the demand of electricity; however, the end result of meeting the increased demand of electricity is achieved regardless of the mechanism.

Another channel through which gas prices could affect utilities' load management programs is through costs. There are three main categories of costs related to load management programs – incentive payments, direct costs, and indirect costs. Incentive payments are monetary payments the utility gives to their customers for their participation in the load management program and to voluntarily curtail their demand during peak hours of the day. Direct costs exclude incentive payments and are the costs of implementing load management programs incurred by the utility. The indirect costs account for administrative costs, marketing costs, and other costs that could not be identified with any particular DSM program category. If there is substitution between natural gas generation and load management programs, one would expect a decrease in natural gas prices to lead to a decrease in incentive payments and direct costs related to load management.

2.3 Previous Literature

The literature on load management programs has been varied and mostly theoretical due to the limited experiments and residential programs conducted in the United States. In the section that follows, a summary of the existing research on LM programs in the United States is provided. Additionally, some of the empirical evidence related to how residential consumers behave in response to these types of programs around the country is examined.

Joskow (2006) discusses the U.S. electricity market and describes some of the market imperfections and institutional constraints that have caused peak wholesale prices and operating reserves to be below their efficient levels. Regarding demand response, the study asserts that demand response should be integrated into the system in a way that is symmetrical to the treatment of supplies of energy, operating reserves, and capacity. Additionally, Joskow (2006) discusses the theory of DR, including pricing and the best way to compensate for DR activity.

To test the impact of DR programs on residential customer behavior, several pilot programs and experiments have been conducted in different areas of the United States. Faruqui and Sergici (2010) provides a review of current existing demand response and dynamic pricing programs around the country. It also provides a survey of the empirical evidence, focusing on fifteen "pilot programs, experiments and full-scale implementations of dynamic pricing of electricity" (Faruqui and Sergici, p. 2). Dynamic pricing refers to allowing the price of electricity to vary with the cost of electricity. Customers are charged a higher amount during peak periods when there is a higher demand for electricity, and a lower amount during off-peak periods when there are fewer customers using energy. The pilot programs described by Faruqui and Sergici vary in their scope and geographic location.

The study's findings show that residential customers on the household level respond to higher prices by lowering their electricity usage. The magnitude of price response varies depending on different factors, including "the magnitude of the price increase, the presence of air conditioning and the availability of enabling technologies such as two-way programmable communicating thermostats and always-on gateway systems that allow multiple end-uses to be controlled remotely" (Faruqui and Sergici, p. 2). As a result, time-of-use rates, where customers are charged a higher price during peak periods and a lower price in off-peak periods, lead to a decrease in peak demand between 3 to 6 percent. Time-of-use pricing differs from real-time pricing because time-of-use pricing varies with peak and off-peak periods, but real-time pricing changes more frequently, at an hourly rate. Critical-peak pricing (CPP) tariffs are pricing schemes with a similar structure to time-of-use rates. One of the main differences is that customers are charged a different, higher rate during CPP events. CPP events occur when the electricity grid is extremely strained due to high demand and are usually caused by increased air-conditioning use on hot summer days or an unexpected electricity outage.[18] Customers are told in advance about the CPP events, which helps them shift their demand to off-peak periods if that is what is desirable to them. Faruqui and Sergici find that CPP tariffs lead to a drop in peak demand between 13 to 20 percent. When pairing these pricing schemes with additional enabling technologies such as a home climate control system or a two-way communicating smart thermostat, the corresponding decrease in demand is even larger. The peak demand declines associated with critical-peak pricing tariffs range from 27 to 44 percent.

One specific example of a demand response experiment is the Pacific Northwest GridWise Demonstration Project. The Pacific Northwest National Laboratory, along with regional utilities and industry partners, conducted the Pacific Northwest GridWise Demonstration Project, which consisted of two separate DR studies: The Grid Friendly Appliance Project and the Olympic Peninsula Project.[19] These projects collected data from March 2006 to March 2007 and tested smart grid technologies as well as whether consumers would play an active role in managing their energy consumption on the grid.

The Grid Friendly Appliance Project installed a controller in 150 dryers and water heaters in homes in Yakima, Washington; Portland, Oregon; and the Olympic Peninsula in Washington.

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[18] Details about CPP events are available at https://www.sdge.com/sites/default/files/documents/cpp_factsheet.pdf
[19] Additional information is available online at the Pacific Northwest National Laboratory website.

This project found that everyday household appliances can automatically reduce energy consumption at critical moments when they are fitted with controllers that sense stress on the grid. Meanwhile, the Olympic Peninsula Project, which consisted of 112 residential homes, found that homeowners are willing to adjust their individual energy use based on price signals provided via information technology tools. Overall, the actions taken in both studies helped reduce pressure on the grid during times of peak demand, potentially preventing power outages during grid emergencies. With these new technologies helping to integrate renewable energy onto the grid and reducing energy consumption during peak time periods, there is a projected $70 billion reduction of new generation, transmission and distribution systems over a 20-year period.

While the literature is growing due to experimental programs around the country, the literature lacks empirical analyses of the motivation behind utilities' usage of DSM programs, particularly load management programs. This paper seeks to fill in the gaps in the literature and provide an understanding of when utilities would use and maintain these programs.

2.4 Theory

Utilities operate with the goal of cost minimization. Therefore, a utility will minimize its costs subject to certain constraints. The main constraint for a utility is supplying enough electricity to meet the demand in each hour. Its costs consist of fixed costs and variable costs. The fixed costs are paid at one time and are not recurring. For example, once a utility purchases a power plant, it may continue to make payments on it, but the purchase of the power plant occurs at one point in time. On the other hand, variable costs include costs that are subject to changes, such as fuel costs and various other operating and maintenance costs. This is where a utility can lower its total costs.

When determining whether to run a natural gas power plant or to employ a LM program to meet its peak demand, a utility must take into consideration the different costs associated with each choice. If the utility already has a natural gas power plant in its generation fleet, it only needs to consider the cost of natural gas and any other variable costs, such as paying workers to make sure the plant runs smoothly. If a utility has already set up a LM program, the only variable costs are the incentive payments it would need to pay out to get customers to curb their energy use during peak hours. Taking costs for both choices into consideration, if the cost of running the natural gas plant is lower than the cost of the LM program, then the utility will choose to use natural gas generation to meet its peak power needs. Alternatively, if the price of natural gas is very high and it is cheaper to use a load management program, then the utility will employ its program instead of running its gas plants.

Assume there are two time periods for electricity usage – a peak period (where the quantity demanded and price of electricity are higher) and an off-peak period (where the quantity demanded and the price of electricity are lower). Each utility is subject to the constraint where the quantity of electricity supplied must equal the quantity of electricity demanded at all times. If this constraint does not hold and electricity demand is not met, then there will be blackouts. In this simple model, electricity is only generated by gas generation or saved through load management programs. In this model, the supply and demand constraints for the peak and off-peak periods, respectively, are:

[1] $$Q_1 = \bar{Q}_1 - \Delta$$
[2] $$Q_2 = \bar{Q}_2 + \Delta$$

Where Δ represents the load management shift (in MW), Q_1 is equal to the amount of electricity generated in the peak period, $\bar{Q}_1$ is the amount of electricity demanded in the peak period, Q_2 is equal to the amount of electricity generated in the off-peak period, and $\bar{Q}_2$ is the amount of electricity demanded in the off-peak period. The quantity of electricity generated in the peak period consists of baseload electricity and peak electricity, and can be represented as:

[3] $Q_1 = \hat{Q}_1^B + Q_1^P$

In equation [3], $\hat{Q}_1^B$ is the amount of baseload electricity generated and Q_1^P is the peak electricity generated in the peak period. In the off-peak period, only baseload power is produced.

Assuming that short-run costs are comprised only of costs related to gas generation and load management, they can be expressed as:

[4] $SRC = C^B(\hat{Q}_1^B, P_G) + C^P(Q_1 - \hat{Q}_1^B, P_G) + C^B(Q_2, P_G) + C^{LM}(\Delta)$

The costs associated with peak period gas generation, consists of two parts: C^B is a function of the quantity of baseload electricity generated in the peak period, $\hat{Q}_1^B$, and C^P is a function of $Q_1 - \hat{Q}_1^B$. In the off-period period, the cost of gas generation, C^B, is a function of the quantity of baseload electricity generated in that period, Q_2. In both the peak and off-peak periods, the costs are also a function of the price of natural gas, P_G. The LM costs, C^{LM}, are a function of the amount of load that is reduced, Δ.

Then the Lagrangian for the cost minimization problem is:

[5] $L = C^B(\hat{Q}_1^B, P_G) + C^P(Q_1 - \hat{Q}_1^B, P_G) + C^B(Q_2, P_G) + C^{LM}(\Delta) + \lambda(\bar{Q}^1 - Q_G^1 - \Delta) + M(\bar{Q}^2 - Q_G^2 + \Delta)$

The first-order conditions from this Lagrangian are:

[6] $\frac{\partial C^P}{\partial Q_1} - \lambda = 0$

[7] $\frac{\partial C^B}{\partial Q_2} - M = 0$

[8] $\frac{\partial C^{LM}}{\partial \Delta} - \lambda + M = 0$

After rearranging the terms in the two first-order conditions above:

[9] $$\lambda = \frac{\partial C^P}{\partial Q_1}$$

[10] $$M = \frac{\partial C^B}{\partial Q_2}$$

Putting these two terms into the third first-order condition and rearranging terms:

[11] $$\frac{\partial C^{LM}}{\partial \Delta} = \frac{\partial C^P}{\partial Q_1} - \frac{\partial C^B}{\partial Q_2}$$

Equation [11] implies that a change in LM costs equals savings in generation.

Using total differentiation, the above equation becomes:

[12] $$\frac{\partial^2 C^{LM}}{\partial \Delta^2}\, d\Delta = \frac{\partial^2 C^P}{\partial Q_1 \partial P_G}\, dP_G + \frac{\partial^2 C^P}{\partial {Q_1}^2}\, dQ_1 - \frac{\partial^2 C^B}{\partial Q_2 \partial P_G}\, dP_G - \frac{\partial^2 C^B}{\partial {Q_2}^2}\, dQ_G^2$$

From the constraints:

[13] $$dQ_G^1 = -d\Delta$$
[14] $$dQ_G^2 = d\Delta$$

And from both of these conditions:

[15] $$dQ_G^1 + dQ_G^2 = 0$$

Substituting this into the equation after total differentiation yields:

[16] $$\left(\frac{\partial^2 C^P}{\partial Q_1 \partial P_G} - \frac{\partial^2 C^B}{\partial Q_2 \partial P_G}\right) dP_G = \frac{\partial^2 C^{LM}}{\partial \Delta^2}\, d\Delta + \frac{\partial^2 C^P}{\partial {Q_1}^2}\, d\Delta + \frac{\partial^2 C^B}{\partial {Q_2}^2}\, d\Delta$$

After grouping like terms and rearranging them:

[17] $$\frac{d\Delta}{dP_G} = \frac{\frac{\partial^2 C^P}{\partial Q_1 \partial P_G} - \frac{\partial^2 C^B}{\partial Q_2 \partial P_G}}{\frac{\partial^2 C^{LM}}{\partial \Delta^2} + \frac{\partial^2 C^P}{\partial {Q_1}^2} + \frac{\partial^2 C^B}{\partial {Q_2}^2}}$$

This expression explains what happens to the amount of load management shifted when there is a change in the price of natural gas. After signing each of the individual components, the expression is positive. The numerator will be positive because during period 1 (the peak period) less efficient units are used as the marginal units. This will cause costs in period 1 to go up more than the costs in period 2 (the off-peak period). In the off-peak period, the marginal unit is usually a combined cycle unit while in the peak period, it is a single peaking unit. The peaking unit burns about 1.5 times the amount of fuel as the combined cycle unit.

In the denominator, the second order terms with respect to Q will be positive if there the cost curves are convex. There should be no change in marginal costs when moving from off-peak to peak periods. The second derivative with respect to Δ is also positive if a convex cost function is assumed. When thinking about the magnitudes of the numerator versus the denominator, if the two terms in the numerator are similar (so that the numerator is small) or if the denominator is large, then utilities will have less of an incentive to do load management. With the expression in equation [17] expected to be positive, this means that the model predicts that an increase in the price of natural gas will lead to an increase in the amount of load management performed. Conversely, a decrease in natural gas prices will lead to a decline in load management activity.

2.5 Data

Every year, the U.S. Energy Information Administration (EIA) collects data from electric utilities about various aspects of their electric power production. Congress mandated the data collection "to promote sound policymaking, efficient markets, and public understanding".[20] The data are summarized and included in EIA publications such as *Electric Power Monthly* and *Electric Power Annual*. The survey is used to collect data on roughly 3,300 respondents. Of that number, approximately 3,200 are electric utilities while 100 are nontraditional entities such as energy service providers or the unregulated subsidiaries of electric utilities and power marketers.

[20] http://205.254.135.24/cneaf/electricity/page/data.html

This paper uses DSM program data from EIA 861 forms, which are the "Annual Electric Power Industry Data Files". These forms include information on annual generation, retail revenue, sales, number of customers, and demand side management program details at the utility level. The forms also have data on time-invariant utility characteristics, such as location and ownership type. The variables of interest that are related to company-administered load management programs include potential peak reductions, actual peak reductions, and program costs. Potential peak reductions reflect "the installed load reduction capability, in megawatts (MW), of program participants during the time of system peak" (U.S. DOE, Benefits of Demand Response and Recommendations, p. 10). Actual peak reduction reflects "the changes in the demand for electricity resulting from a load management program that is in effect at the same time that the utility experiences its annual peak load" (U.S. DOE, Benefits of Demand Response and Recommendations, p. 10). The program costs consist of both direct and indirect utility expenses, including program administration, payments to participants, and marketing. However, costs reported to the EIA do not include those incurred directly by participating customers. The EIA forms also collect data on load management incentive payments, which are payments by the utility to the customer for load management activities. Additionally, each utility is assigned a unique identification number, which is consistent from one year to the next and across various EIA forms.

The EIA 861 forms were implemented in January 1985, and the EIA started collecting data as of year-end 1984. The data are publically available on the EIA website from 1990 to 2010. The forms also report DSM activity broken down by sector. There are four different sector classifications: residential, commercial, industrial, and other (includes transportation). Beginning in 2010, the DSM data were reported by utility and state, adding another layer of detail into the data. In 2010, there were 35 multi-state utilities, while in 2011 there were 39 utilities of this type.

The sample used for this analysis contains data from 2001 through 2011, and only includes utilities that fill out the EIA 861 Form 3, which contains information on the DSM measures. Furthermore, only utilities with certain ownership types are kept, which are then classified into three groups – private, local government, and cooperative. The private group consists of investor-owned utilities and retail power marketers; the local government group contains municipal, municipal marketing authority, and political subdivision utilities; and the cooperative group is made up of cooperative utilities. The utilities that are classified with ownership types of federal, state, transmission, or other, are excluded from my sample.

In addition to narrowing the sample based on ownership type, any utilities that have negative values for the DSM measures are dropped from the sample. This eliminates two utilities from the sample. Observations where the amount of actual load management peak reduction exceeds the maximum load for the year are also excluded from the sample since it is unrealistic for utilities to reduce their load in an amount greater than the maximum amount of electricity demanded during that year. There are only three observations in the dataset where these peak reductions are greater than maximum load. The final dataset includes 1,395 unique utilities and 9,574 observations in an unbalanced panel dataset. The amount of time that each utility is in the dataset varies, with 25 percent of utilities being in the dataset for the entire time period.

Table 2.1 shows the total amount of load management activity by year, separating out potential peak load reductions (in MW) and actual peak load reductions (in MW) from 2001 through 2011. It also shows each of these variables normalized by peak summer demand (in

MW). These numbers are calculated using the EIA 861 forms described above. This table shows that the total amount of potential peak reductions in the first column decreased from 2001 through 2004 and then increased from 2005 through 2011. The total amount of actual peak reductions displayed in the second column followed a similar pattern, decreasing from 2001 through 2003 before mostly rising again from 2004 through 2011. If the potential and actual reductions are normalized using peak summer demand (in MW), I get measures for program capacity and utilization, respectively. These measures are shown in the third and fourth columns of Table 2.1. Program capacity decreases steadily from 2001 through 2004. After that, program capacity fluctuates up and down and there isn't a clear trend during the remaining time period. The annual values for program utilization also show a steady decline from 2001 through 2004, then some fluctuations in 2005 and 2006 before stabilizing from 2007 through 2010. Following this period of stability, program utilization declines slightly in 2011.

Calculating program usage and capacity based on the percentage of summer peak is a good indication of how much load management a utility is using and the size of each utility's program. It also allows for the comparison of the usage and capacity of LM programs among utilities of different sizes. For example, say Utility A has a peak summer demand of 10 MW and has actual annual peak LM reductions of 2 MW, then its program utilization is 0.2, or 20 percent. Utility B could have a peak summer demand of 100 MW and actual annual peak LM reductions of 20 MW. Using those numbers, Utility B has the same program utilization as Utility A (20 percent), even though the absolute amount of LM reductions done by Utility B is 10 times the amount done by Utility A. For the purpose of this analysis, the amount of LM reductions has been normalized using the historic peak summer demand from the data for each utility.

As mentioned in the data description earlier in this section, these forms also include information on the direct and indirect costs of DSM programs. As the amount of DSM activity has increased from 2001 to 2011, the total DSM costs during this same time period grew as well from roughly $1.2 billion in 2001 to $4.7 billion in 2011.[21] Since the amount of potential peak reductions from 2001 and 2011 declined, the increases in total costs could have been due to program set-up becoming more expensive or changes to programs other than load management during that time period.

Table 2.2 displays summary statistics for the entire sample, and Tables 2.3a and 2.3b split the sample based on treatment and comparison groups. Table 2.3a contains the data for non-private utilities and Table 2.3b displays the summary statistics for private utilities. The treatment group consists of utilities that ever generate electricity, while the comparison group has utilities that do not generate electricity. The methodology section below explains additional details about these two groups. Tables 2.3a and 2.3b show that the treatment group is made up of utilities that are bigger in terms of peak summer demand and retail revenues.[22] Although the group of utilities that generate electricity do a larger amount of load management (based on both the actual and potential reductions measures), they also have a larger peak summer demand. As a result, the mean values of load management as a percentage of the utility's peak summer demand are closer between the two groups. The summary statistics tables also show that, on average, utilities do not do much load management, which is understandable since they would only employ these programs during the peak hours of the year when electricity demand is very high.

[21] Total costs are in 2013 real dollars.
[22] Retail revenues have been converted to real 2013 dollars.

2.6 Methodology

To test the impact of lower gas prices on the usage and size of existing programs (in MW), a difference-in-differences estimation technique is used. The decline in natural gas prices after 2008 divides the sample into two periods, and can be used as an exogenous event because the decrease was due to technological improvements in obtaining natural gas. The amount of U.S. gas shale production increased significantly after 2008, leading to lower natural gas prices.[23] For this analysis, the post-period is the time period after the decline in gas prices, 2009 – 2011 and the pre-period is the time period prior to the gas price decline, 2001 – 2008. Figure 2.3 shows the trend in U.S. natural gas citygate prices from 2001 through 2013. While the gas price is volatile throughout that time period, there is a sharp decline in prices after 2008. In addition to a drop in natural gas prices after 2008, the volatility in the price also declined. Prior to and including 2008, the average annual coefficient of variation was 0.14, while after 2008, it dropped to 0.08. With gas prices becoming more stable following 2008, this could change utilities' long-term expectations regarding price levels, the variability of gas prices due to technology, natural gas generation, and the usage of their load management programs.

The change in natural gas prices was due to an increase in domestic natural gas supply, which was obtained via advancements in technology. Figure 2.4 uses data from the EIA and shows the amount of monthly dry shale gas production by location for 2001 through 2013. There is a sharp increase in production after 2008, which coincides with the decrease in natural gas prices in Figure 2.3. With new technology and as fracking became more prevalent, not only did the amount of natural gas supplied increase, but natural gas obtained through conventional production types, such as gas and oil wells declined. As shown in Figure 2.5, the amount of

[23] For more information on the trends in natural gas productions and prices, see http://www.eia.gov/pressroom/presentations/newell_02082011.pdf

natural gas procured through shale gas increased substantially after 2008, while at the same time production through gas wells and oil wells significantly declined even though total production increased.

For the purpose of the analysis, there are two different groups of utilities: the treatment group consists of utilities with any reported generation from 2001 through 2011 and the comparison group consists of utilities without any generation. Utilities that have their own generating facilities have much more control over the generating source of the electricity that they sell. Such utilities can more easily decide to run a plant to generate electricity rather than employ a load management program when gas prices are low and energy demand is high. Alternatively, utilities without generation capabilities are limited to buying power on the wholesale market and cannot substitute natural gas generation and load management programs as easily.

Furthermore, the sample is divided based on whether the utilities are private or non-private (not for profit) and separate regressions are run for these two categories of utilities. The non-private utility group is made up of utilities with ownership type of cooperative or local government. These utilities act with the goal of output maximization and they want to serve as many customers as possible with the lowest cost. Private utilities are often subjected to different regulatory restrictions than non-private utilities. They are regulated by state public utility commissions (PUCs) and their retail rates need to be approved by the PUCs. For this reason, they may respond differently to a decrease in natural gas prices and their load management program usage and capacity may vary from the actions of non-private utilities. Therefore, these two categories of utilities are separated for the purpose of this analysis.

The dependent variable of interest is a measure of load management activity done by each utility in the sample. For the purpose of this analysis, there are two different dependent variables of interest. The first is the actual load management peak reductions (in MW) divided by historic peak summer demand (in MW). This is a measure of program utilization – how much of the load management program a utility uses as a percentage of its summer load. Historic load is defined as the load in the first year of data in the sample that is available. The second variable of interest is the potential load management peak reductions (in MW) divided by historic peak summer demand (in MW), which is a measure of the size of the utility's program as a percentage of its summer load. Going forward, these variables will be referred to as "program utilization" and "program capacity", respectively.

To estimate the difference-in-differences regression, panel data will be used. The regression can be written as:

[18] $$LM_{it} = \alpha + \beta_1 Gen\ Ever + \beta_2 Postperiod + \beta_3 Gen\ Ever * Postperiod + \gamma X + \varepsilon_{it}$$

The dependent variable, "LM", is either program utilization or program capacity. The "Gen Ever" variable is a dummy variable that equals 1 if the utility ever generates any electricity, and 0 otherwise. This is the definition that is used for the treatment group. The "Postperiod" variable is a dummy variable that equals 1 if the year is greater than 2008, and equals 0 if the year is less than or equal to 2008. The vector X represents control variables used in this regression, including each utility's annual retail revenues, and a dummy variable for its state of operation.

The change based on the treatment will be captured by the coefficient on the interaction term, β_3, and the expected sign on β_3 is negative. For example, if utilities are truly treating natural gas and load management programs as substitutes, one would expect that a decline in natural gas prices will decrease the usage of LM programs. If utilities find it cheaper to run their natural gas plants than to employ their LM programs and give incentive payments to the customers of their load management programs, then they will decrease usage of these programs. The expected sign when examining the capacity of LM programs is more ambiguous. A short-term decline in natural gas prices may have no impact on the size of LM programs if the programs are already in place. Additionally, utilities may be less likely to abandon programs that they have already invested a fixed amount of money in – they would only decrease the amount they use the programs. However, program capacity could also decrease if utilities decide to shrink their programs once they are not utilizing them as much as before.

2.7 Results

2.7.1 Results for Non-Private Utilities

Table 2.4a displays the results of estimating equation [18] when the regression is run for non-private utilities and the dependent variable is program usage. The different columns in Table 2.4a represent the various specifications of the regression. Column [1] presents the results for the regression when it is run without any controls. Column [2] adds in a control variable for retail revenues, while Column [3] adds in the state dummies. Standard errors are clustered by utility. As expected, the coefficient on the interaction term between Gen Ever and Post is negative and statistically significant at the 1 percent significance level for all specifications in Table 2.4a. This means that after the decline in gas prices, non-private utilities that generated their own electricity reduced their usage of load management programs. This makes intuitive sense and is in line with the hypothesis that utilities are using gas generation and load management programs as substitutes when they generate their own electricity.

Looking more closely at Table 2.4a, the results indicate that following a gas price decrease, utilities with generation will decrease their usage of the load management programs by 1.51 percent to 1.95 percent of their peak summer demand, depending on the specification. With gas prices at a lower level, utilities may choose to employ natural gas generation to meet their peak demand, rather than using their LM programs. The usage of LM programs can be viewed as a short-run decision for the utility. The magnitudes of the coefficients on the interaction term between the utilities that generate and the post-period do not change very much across each of the specifications.

Table 2.4b presents the results when using program capacity as the dependent variable. The columns are laid out in a similar fashion as Table 2.4a. Column [1] contains the results for the simplest regression without any controls. Column [2] adds in a control variable for retail revenues, and Column [3] adds in the state dummies. Again, standard errors are clustered by utility. Table 2.4b measures the change in the size or capacity of the program after a gas price decrease. Here, all the results are negative and statistically significant at the 1 percent level. The results show that non-private utilities with generation decrease the size of their programs by 4.49 percent to 5.18 percent of their peak summer demand. Contrary to program utilization, which is a short-run decision for the utility, program capacity is a long-run decision for the utility. A utility can decide on the size of its LM program and keep it constant for several years even though LM program usage can vary from year to year.

Based on the results in Table 2.4b, there is a larger decline in the capacity of the LM programs compared to the change in the utilization of these programs following a decrease in gas prices. This is consistent with a declining option value due to decreasing gas prices and lower volatility. Having a LM program is valuable to a utility and it has the option to use the LM program instead of running its gas generation plants to meet peak demand. However, when gas prices are falling and the volatility has decreased, a utility is less likely to use its program and if it does use its program, the utility will use it less often. Across the different specifications for the program capacity regressions, there is little variation in the magnitudes of the coefficients. If utilities expected natural gas prices to remain lower and more stable following the decrease in gas prices, then they would not have increased the size of their programs after 2008. The results in Table 2.4b appear to support this hypothesis.[24]

The results presented in Tables 2.4a and 2.4b support the prediction of the model in the theory section of this paper. When there is a decrease in the price of natural gas, utilities that generate electricity will decrease their load management program usage and program capacity relative to the utilities that do not have the capability to generate electricity. This supports the notion that utilities are using these programs for cost minimization reasons.

2.7.2 Results for Private Utilities

To determine whether private utilities are also motivated by cost minimization to use and maintain the size of their load management programs, the regression is run separately for private utilities. The results are presented in Tables 2.5a and 2.5b, with the dependent variables as program usage and program capacity, respectively. In both tables, the columns represent different specifications. Column [1] presents the results for the regression when it is run without any controls and Column [2] adds in a control variable for retail revenues. Column [3] includes a variable to indicate whether the utility is in a state with deregulated electricity markets. In a

[24] The analysis was repeated using direct costs related to load management as the dependent variable. The results using that variable are insignificant. However, it is important to note that for utilities that operate both load management and energy efficiency programs, it is difficult to disentangle the costs and attribute some to load management costs and others to energy efficiency costs. For this reason, the analysis is omitted from this paper, but the results available upon request. The analysis was also done for utilities that only have load management programs, and the results are also available upon request.

deregulated electricity market, a monopoly system of electric utilities has been replaced with competing sellers.[25] Column [4] does not include the deregulation flag variable, but takes the specification in Column [2] and adds in the state dummies. Standard errors are clustered by utility. From Table 2.5a, the program usage results show that, unlike the results for non-private utilities, the coefficient on the interaction term for the private utilities regression is positive and not statistically significant. The magnitude is approximately 2 percent of peak summer demand and does not vary much across the different specifications.

Similarly, the results for LM program capacity in Table 2.5b are also positive and not statistically significant. The magnitudes of the coefficient on the interaction term ranges from 1.26 percent to 1.77 percent of peak summer demand, depending on the specification. Again, this result for the private utilities differs from the result for non-private utilities displayed in Table 2.4b. The coefficient on the interaction term in the specification which includes the deregulation variable is slightly smaller in magnitude than the coefficients in the other specifications. The coefficient on the deregulation variable in that specification is negative and statistically significant at the 10 percent level. This means that private utilities that are in deregulated states are more likely to decrease their LM program size.

Based on the results in Tables 2.5a and 2.5b, it appears that private utilities have a different motivation when using and maintaining the size of their load management programs than non-private utilities. After a decrease in gas prices, there is not a statistically significant response in private utilities' LM program usage and capacity. The results presented in Tables 2.4a and 2.4b support the hypothesis of cost minimization for non-private utilities; however, the estimates for private utilities seen in Tables 2.5a and 2.5b indicate that while cost minimization

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[25] For a map of U.S. states that have deregulated electricity markets, see http://www.eia.gov/electricity/policies/restructuring/restructure_elect.html

may be occurring, any impact may be overwhelmed by other forces, such as regulatory pressure. Private utilities may choose not to cost-minimize due to regulations by public utility commissions. Non-private utilities are not subject to the same constraints and when the gas price declines, they may be able to adjust their LM program usage and capacity to reflect cost minimization.

2.8 Conclusion and Policy Implications

As demand side management programs become more popular in the United States, it becomes more important to understand what they do and how they work. This study fills a hole in the empirical literature by examining why utilities are motivated to use and maintain load management programs. Previous literature in this area has focused primarily on the theoretical aspects of demand response, where these programs fit in to the current supply and demand model for the electricity market, and cost-benefit analyses of existing programs. Further, there have been papers which have described in great detail some of the prior pilot programs and experiments involving demand response around the country. My goal is to determine why some utilities embrace and develop demand side management programs, while others do not invest in these types of programs.

This paper utilizes data from the past decade to analyze whether a decline in natural gas prices impacts utilities' load management usage and capacity. A gas price decline is used to examine whether utilities are motivated by cost minimization. This study exploits a sharp exogenous decrease in natural gas prices and employs a difference-in-differences estimation technique. I determine that for non-private utilities, gas prices have a negative and statistically significant relationship with both the usage of load management programs and the size of existing programs if the utility generates its own electricity. Utilities with generation will decrease their usage of load management programs by 1.51 percent to 1.95 percent of their peak summer demand compared to non-generating utilities. The result for program capacity is larger in magnitude. Utilities with generation decrease the size of their programs by 4.49 percent to 5.18 percent of their peak summer demand relative to the comparison group. The results for private utilities are not statistically significant.

The results for non-private utilities provide supporting evidence for the hypothesis of substitutability between gas generation and load management programs, and that utilities may do so for cost minimization reasons. A competing hypothesis is that utilities may choose to adopt these programs due to pressure from regulatory agencies. While private utilities could be exhibiting some cost minimization behavior, it may be overwhelmed by regulatory pressure, which leads to an insignificant result. The hypothesis regarding regulatory pressure could be an area for future research.

Understanding why some utilities adopt, use, and maintain DSM programs is important not only to the utilities themselves, but also to policymakers and the public at large. As more DSM programs are developed and used throughout the country, they will continue to play an important role in balancing electricity supply and demand. Moreover, the development and growth of effective demand side management programs can lead policymakers and utilities to find an alternative solution to building expensive new generation plants to meet the growing energy needs of the United States.

3. Electricity Market Deregulation and Electric Utilities' Energy Efficiency Activity

3.1 Introduction

Over the last twenty years, concerns about energy consumption, climate change, and higher electricity prices in the United States have led to energy conservation efforts. The United States government has developed several policies to encourage energy conservation through energy efficiency programs. Federal programs include the Corporate Average Fuel Economy Standards, the Weatherization Assistance Program (WAP), and the Federal Hybrid Vehicle Tax Credit. At the state and local level, there are utility-run electricity demand side management (DSM) programs.

Energy efficiency programs are energy conservation programs which decrease the usage of electricity during all hours of the day. They fall into a broad group of energy conservation programs which are termed *demand side management (DSM) programs*. Several DSM programs in the United States were started in response to the energy crises in 1973 and 1979 and were pushed by regulators as money saving measures for rate payers. While these programs have been in place for a few decades, there has been renewed interest in these types of programs following the California Electricity Crisis in the early 2000s, electricity market deregulation, and the increasing energy prices across the country during the last decade. DSM programs have been used in the industrial sector, but the recent push has been for implementation at the residential customer level.

Energy efficiency programs are becoming increasingly popular due to environmental concerns. In 2012, the electricity sector was responsible for 32 percent of greenhouse gas (GHG) emissions in the United States, making it the largest source of GHG emissions in the

U.S.[26] It was also the single largest source of carbon dioxide (CO_2) emissions in the U.S., contributing 38 percent of the nation's total CO_2 emissions.[27] Additionally, the Environmental Protection Agency (EPA) proposed the Clean Power Plan in June 2014 to cut carbon emissions from existing plants. Each state is given a state-specific goal for carbon reduction by 2030, which is calculated as "CO_2 emissions from fossil fuel-fired power plants in pounds (lbs) divided by state electricity generation from fossil-fuel fired power plants and certain low- or zero-emitting power sources in megawatt hours (MWh)".[28] The EPA is letting each state decide how it wants to meet its carbon reduction targets. Megawatt-hour savings from energy efficiency are explicitly listed as factoring into the denominator to calculate this rate. Therefore, energy efficiency programs may play a significant role in helping to reduce the carbon emissions in the United States.

This paper analyzes the impact of regulation on electric utilities' energy efficiency programs. It exploits a change in states' regulatory status in the late 1990s and early 2000s. This shift to deregulation occurred in some states, but not in others. Additionally, deregulation impacted private utilities more than non-private utilities because private utilities are subject to stricter regulations from their state's public utilities commissions (PUCs). This paper employs a triple difference model in order to determine the impact of deregulation on energy efficiency activity.

Following the deregulation of electricity markets, private utilities decreased their energy efficiency activity by approximately 200,000 MWh per utility. This is a large amount of activity, which is roughly equivalent to a natural gas plant running at full capacity for an entire year. The

[26] http://www.epa.gov/climatechange/ghgemissions/sources/electricity.html
[27] http://www.epa.gov/climatechange/ghgemissions/gases/co2.html
[28] For more information on the EPA Clean Power Plan, see http://www2.epa.gov/carbon-pollution-standards/fact-sheet-clean-power-plan-framework

results in this paper support the notion that utilities are under regulatory pressure to make energy efficiency investments and this may be the motivation behind their energy efficiency activity.

The rest of the paper proceeds as follows. The next section provides additional background information about energy efficiency programs and the history of electricity market deregulation in the United States. Then the previous literature on energy efficiency is summarized. After that, the methodology and data used in this analysis are discussed. The results follow in the subsequent section, and then the paper concludes and offers some policy implications.

3.2 Background

3.2.1 Energy Efficiency Programs

Demand side management (DSM) programs encompass both load management (LM) and energy efficiency (EE) activity. Generally, load management refers to activities to curb energy consumption during the peak hours of the day or during high price periods. They are sometimes referred to as demand response (DR) programs. Utilities will pay customers a dollar amount (usually per MW) for voluntarily decreasing their demand during peak hours of the day. Energy efficiency (EE), on the other hand, refers to efforts to reduce the amount of energy required to do certain activities and typically involves energy conservation across all hours of the day not just during peak periods. For example, replacing traditional light bulbs with fluorescent ones that give the same amount of illumination is an energy efficiency action. For an action to qualify as an energy efficiency activity by a utility, the utility needs to invest in the capital cost of the project. Regulators allow utilities to include energy efficiency activities in their rate base.

Therefore, utilities can charge electricity prices that would earn them a rate of return on their investments and in turn, rate payers are paying for the programs.

Using data from the New York Independent System Operator (NYISO), which runs the electricity grid in New York State, Figure 3.1 shows how the hourly load curve changes with the implementation of a hypothetical energy efficiency program. The solid blue line represents the actual load data for July 19, 2013 and the dashed orange line represents an EE program that reduces energy usage by 5 percent. With an EE program in place, the hourly load curve has decreased during every hour of the day. The focus of this paper is energy efficiency programs, and the motivation behind load management program usage is discussed in Chapter 1. This paper also does not explore other types of energy efficiency policies that do not apply directly to utilities. Examples of these policies include incentives to improve household appliances and credits for purchasing low-emissions vehicles.

3.2.2 Electricity Market Deregulation

Traditionally, electricity was provided by utilities to customers in their service area. State governments established public utilities commissions (PUCs) to regulate and oversee the energy industry. In addition to ensuring that electricity was provided reliably, the PUCs made sure that electric prices were fair. The regulation of electricity markets led to monopolies in the industry, with utilities having control over all processes of electricity generation, transmission, and distribution. In the mid-1990s, many states looked into expanding competition in their electricity markets, believing that consumers would receive better prices with the relaxation of the monopolies. This led to electricity market deregulation in several states. Prior federal rule changes had allowed competition in the wholesale market, but the state level restructuring deregulated the retail rates and let consumers have direct access to wholesale suppliers.

The structure of a traditional utility in a regulated market is characterized by the utility being primarily responsible for its own generation, transmission, and distribution of electricity to all the retail customers in its service territory. After deregulation, most utilities unbundled their generation processes. Utilities divested their assets, separating their generation facilities from transmission and distribution assets. Vertically integrated utilities were replaced with new institutions managed by all market participants. Deregulation also led to the creation of new entities, such as Independent System Operators (ISOs), who coordinate the purchase of power and transmission scheduling. Additionally in deregulated markets, customers have choices and can purchase power from any of the suppliers on the grid. Market prices replaced government regulation of the energy portion of utility rates, making prices more competitive. Currently, even between states that have deregulated electricity markets, there are regional differences. Each region varies in their rules concerning the power exchanges and other aspects of their market.[29]

Table 3.1 summarizes the states that deregulated their electricity markets and the year of deregulation activity. According to the U.S. Energy Information Administration (EIA), as of September 2010, 15 states and the District of Columbia had deregulated electricity markets. An additional 7 states had started but suspended their deregulation activity. The earliest states to implement deregulation were Massachusetts, New York, and Rhode Island – they deregulated in 1998. Of the states that deregulated, Michigan, Oregon and Texas were the ones that deregulated latest, doing so in 2002. The other states that experienced a restructuring of their electricity markets all did so in the short time period from 1998 through 2002. Since states have deregulated their electricity markets, there has been mixed evidence as to whether or not electricity market deregulation leads to lower energy prices.

[29] For additional information on the structure of the electric industry before and after deregulation, see the Department of Energy's "A Primer on Electric Utilities, Deregulation, and Restructuring of U.S. Electricity Markets" (2002) and Joskow and Schmalensee's "Markets for Power" (1983).

3.3 Previous Literature

The previous literature related to energy efficiency programs has mostly been cost-benefit analyses and theoretical models. There has been some literature devoted to analyzing the impact of electricity market deregulation on energy prices. This paper fills a void in the empirical literature examining the motivation behind utilities' usage of energy efficiency programs and the role that electricity market deregulation plays in energy efficiency activity.

Arimura, et al (2011) examines the cost effectiveness of electricity energy efficiency programs. The study allows energy efficiency DSM spending to have a potential long-term demand effect and it uses instrumental variables to address the possible endogeneity in spending. The results show that ratepayer-funded DSM expenditures between 1992 and 2006 produced a central estimate of 0.9 percent savings in electricity consumption. The savings come at an expected average cost to the utilities of 5 cents per kWh saved, with a discount rate of 5 percent.

Several authors analyze the energy efficiency gap, or the difference between actual and optimal energy use and whether such a gap exists. Jaffe and Stavins (1994) identifies the major issues in defining optimal energy use and considers energy efficiency as a "means to the end of overall efficient (and equitable) resource allocation". The differing views from technologists and economists on optimal energy use are examined and various levels of economic potential and social optimum for energy efficiency are offered. Alcott and Greenstone (2012) provides a more recent examination of the energy efficiency gap and whether it exists. This paper differentiates between two types of market failures related to energy efficiency – energy use externalities and investment inefficiencies – and separately examines their policy implications. The paper's findings suggest that there is a large amount of heterogeneity in investment inefficiencies and targeted policies would be more effective than general subsidies or mandates.

Both Jaffe and Stavins (1994) and Alcott and Greenstone (2012) provide insights into the optimal level of energy use and how market failures arise. However, the literature on energy efficiency is lacking empirical research related to the motivation of electric utilities' use of these programs. This paper examines electric utilities' behavior related to energy efficiency and looks into whether deregulation impacts their energy efficiency activity.

3.4 Data

The U.S. Energy Information Administration (EIA) collects data from electric utilities and compiles the data in various forms. The EIA 861 forms, or the "Annual Electric Power Industry Data Files", include information on DSM programs and utility characteristics, and the data are collected annually. There are approximately 3,300 respondents every year – roughly 3,200 are electric utilities and 100 are nontraditional entities such as energy service providers or the unregulated subsidiaries of electric utilities and power marketers.

The EIA 861 forms contain data at the utility level and each utility is assigned a unique identification number which is consistent from one year to the next and across various EIA forms. They include information that varies from year to year including peak summer demand, revenues, sales, and demand side management program details. Additionally, the forms have time-invariant information on utility location and ownership type. For this paper, the key variables of interest are related to energy efficiency programs. The energy efficiency "energy effects" variable refers to changes in aggregate electricity use for customers that participate in a utility DSM program and is measured in megawatt hours (MWh). These programs reduce overall electricity consumption and savings are “generally achieved by substituting technically more advanced equipment to produce the same level of end-use services using less electricity”.[30] Some examples of energy efficiency activities include more efficient appliances, lighting, and heating, ventilating and air conditioning (HVAC) systems. The data reported do not indicate the potential amount of energy savings based on these utility programs, but rather the total amount of energy saved in a given year.

The EIA 861 forms were implemented in January 1985, and the EIA started collecting data as of year-end 1984. The data are publically available on the EIA website from 1990 to 2011. The forms also report DSM activity broken down by sector. There are four different sector classifications: residential, commercial, industrial, and other (includes transportation). Beginning in 2010, the DSM data were reported by utility and state, adding another layer of detail into the data. In 2010, there were 35 multi-state utilities, while in 2011 there were 39 utilities of this type.

The sample used for this analysis contains data from 1990 through 2011. Furthermore, only utilities with certain ownership types are kept. These are classified into two main groups – private and non-private (or not for profit). The private group consists of investor-owned utilities and retail power marketers, while the non-private group includes municipal, municipal marketing authority, political subdivision, and cooperative utilities. The utilities that are classified with ownership types of federal, state, transmission, or other, are excluded from the sample.

In addition to narrowing the sample based on ownership type, any utilities that have negative values for the energy efficiency measures are dropped from the sample. This eliminates one utility from the sample. The amount of time that each utility is in the dataset is varied, with

[30] For more information on the data included in the EIA 861 forms, see http://www.eia.gov/electricity/data/eia861/index.html

90 percent of utilities being in the dataset for the entire 22 year time period. As these utilities make up the majority of my sample, and because I want to look at utility behavior both before and after the change in electricity markets, the final dataset only includes utilities that fill out the EIA 861 forms during all 22 years. The final dataset used in this analysis includes 2,827 unique utilities and 62,194 observations in a panel dataset.

Table 3.2 shows the total amount of energy efficiency activity by year from 1990 through 2011. These numbers are calculated using the EIA 861 forms described above. This table shows that the total amount of energy efficiency activity steadily increased from 1990 to 1995 before stabilizing at around 50 TWh of savings during the mid-1990s and into the early 2000s. Starting around 2004, the trend in energy efficiency started increasing again until 2009 when there was a brief decline. Following that year, energy efficiency activity continued increasing until it was approximately 120 TWh in 2011, the last year in my dataset. As a comparison, this is roughly the amount of electricity that is generated by 14 nuclear power plants running at full capacity for a year, and is a large amount of energy saved. It is also approximately 3 percent of total U.S. electricity consumption.

Table 3.3 displays summary statistics for the entire sample, and Table 3.4 splits the sample based on ownership type. The left panel presents the data for non-private utilities and the right panel displays summary statistics for private utilities. All data in this table are for the time period before deregulation occurred. The data in this table indicate that, on average, private utilities are much larger than non-private utilities based on the observable variables of peak summer demand, retail revenues, and energy efficiency activity. Tables 3.5a and 3.5b further split the data based on whether or not the utilities are located in a deregulated state. Table 3.5a contains the data for non-private utilities and Table 3.5b displays the summary statistics for private utilities. The treatment group consists of utilities that are located in deregulated states, while the comparison group contains utilities that are located in states that still have regulated markets. The methodology section below explains additional details about these two groups. Tables 3.5a and 3.5b show that within each ownership type, the utilities on average are similar in terms of the measures of peak summer demand and retail revenues. For private utilities, utilities in states that deregulate their electricity markets have slightly larger peak summer demands and retail revenues, but a smaller amount of energy efficiency activity when compared to utilities in regulated states. For non-private utilities, the reverse is true. Utilities in regulated states have larger peak summer demands and retail revenues, but a lower amount of energy efficiency compared to non-private utilities in deregulated states.

Figures 3.2 and 3.3 represent the time trends for each group, split by whether or not the utilities are in a deregulated state. Figure 3.2 displays what happens to non-private utilities over time and Figure 3.3 shows the trends for private utilities. These graphs show that the utilities in deregulated and regulated states move in similar fashions until around 2000, when most of the state deregulation occurs. Following that, the line for utilities in deregulated states (shown in blue) rises significantly when compared to the line representing utilities in regulated states (the red line). This pattern holds for both the private and non-private utilities.

The data on when states deregulated was collected from various sources online. Each state that transitioned to a deregulated electricity market is listed in Table 3.1 with the date when their electricity market became competitive.

3.5 Methodology

To test the impact of electricity market deregulation on electricity reductions (in MWh), a triple difference, or difference-in-difference-in-differences estimation technique is used. The utilities are split into two groups: those that are located in states that deregulated their electricity markets and those that are located in states with electricity markets that remained regulated during the entire time period.[31] The states that deregulated their electricity markets all did so between 1998 and 2002. In order to cleanly divide the time period in the analysis into a pre-period and a post-period, the data for the years 1998 through 2001 are cut from the sample. Therefore, the pre-period consists of the years from 1990 through 1997, and the post-period includes the years 2002 through 2011. The final dataset includes 18 years of data. Furthermore, utilities are divided based on ownership type. They are classified as either private or non-private (not for profit) utilities. Private utilities are often subjected to different regulatory restrictions than non-private utilities. They are regulated by state public utility commissions (PUCs) and their retail rates need to be approved by the PUCs. For this reason, they may respond differently to a change in state regulatory status their energy efficiency program usage may vary from the actions of non-private utilities.

To estimate the triple difference regression, panel data are used. The regression can be written as:

[19] $EE_{it} = \alpha + \beta_1 Dereg * Priv * Postperiod + \beta_2 Dereg * Priv + \beta_3 Priv * Postperiod + \beta_4 Dereg * Postperiod + \beta_5 Dereg + \beta_6 Priv + \beta_7 Postperiod + \gamma X + \varepsilon_{it}$

[31] Utilities in states that suspended their deregulation activities are placed in the group of that remained regulated because for most of these states, while legislation was passed enacting deregulation, deregulation only went into effect in two states before being suspended. Additionally, putting the "suspended" states into the deregulated states group does not change the results significantly.

The dependent variable of interest is a measure of energy efficiency activity in MWh by each utility in the sample. In a second specification, the natural log of energy efficiency activity is used as the dependent variable. The "Dereg" variable is a dummy variable that equals 1 if the utility is located in a state that has deregulated its electricity market as of September 2010, and 0 otherwise. The "Priv" variable is a dummy variable that equals 1 if the utility lists its ownership type as "Private" in the EIA Form 861, and 0 if the utility reports its ownership type as "Cooperative", "Municipal", or "Political Subdivision". The "Postperiod" variable is a dummy variable that equals 1 if the year is greater than or equal to 2002, and 0 otherwise. The vector X represents control variables used in this regression, including each utility's peak summer demand and retail revenues.

The change based on being a private utility in a deregulated state following restructuring will be captured by the coefficient on the interaction term of the three variables, β_1, and the expected sign on β_1 is negative. Following deregulation, it is expected that private utilities will reduce the amount of energy efficiency that they do. This would be the case if under regulated markets, public utilities commissions required utilities to perform a certain amount of energy efficiency every year. With less regulatory pressure, the utilities may find that it is not in their interest to keep using their energy efficiency programs. If private utilities act as profit maximizers, they need to completely recoup the capital costs that they invested in energy efficiency technology with a high rate of return; otherwise it does not make sense from an economic standpoint for them to do energy efficiency. On the other hand, if utilities act in an altruistic manner and believe that even following deregulation, their public utilities commissions will look more favorably on their distribution rate requests for having and using energy efficiency programs, they may keep using their programs. Additionally, if they have already invested in energy efficient technology, they could keep up the existing level of activity without investing in new technologies.

3.6 Results

3.6.1 Triple Difference Results: Levels

The results of estimating equation [19] from the previous section are presented in Table 3.6. For this regression, the dependent variable is total MWh of energy efficiency reductions. The two columns represent different specifications of the regression. Column [1] includes all the interaction terms and the variables for deregulation, private ownership, and post-period. Standard errors are clustered by utility. The coefficient of interest on the Dereg*Priv*Postperiod variable is negative and statistically significant at the 5 percent level. This suggests that following state deregulation, private utilities decrease their energy efficiency activity by 232 GWh relative to non-private utilities. This is consistent with the intuition in the previous paragraph. Once regulatory pressure is lessened, electric utilities will decrease the amount of energy efficiency activity they perform.

The magnitudes of the results in Table 3.6 are large. They are as large as the average amount of energy efficiency performed by private utilities. Private utilities also performed a larger amount of energy efficiency prior to deregulation. For comparison, the decline in energy efficiency activity per utility is roughly the size of a natural gas power plant running at full capacity for a year.

Column [2] adds in a control variable for peak summer demand. Again, standard errors are clustered by utility. The coefficient on the variable of interest remains negative and is statistically significant at the 10 percent level. The magnitude has decreased and is -201,455

MWh in this specification. This is the preferred specification for the levels regressions. The results are consistent with the hypothesis that private utilities in deregulated states will decrease their energy efficiency activity following electricity market restructuring.

3.6.2 Triple Difference Results: Natural Logs

Table 3.7 repeats the analysis but uses the natural log of energy efficiency annual total MWh as the dependent variable. In order to keep observations with a value of 0 in the dataset, a value of 1 is added to all the energy efficiency MWh values before taking the natural logs. This table has a similar layout to Table 3.6 with Column [1] including all the interaction terms and variables of interest and Column [2] adding in a control variable for the natural log of peak summer demand. This table includes an additional column, Column [3], which includes a control variable for the natural log of retail revenues. The coefficient of interest is negative and statistically significant at the 1 percent level with the magnitude ranging from -2.117 to -2.685. Again, this is a large number, and it implies that electricity market deregulation has important implications for energy efficiency activity. The specification in Column [2] is the preferred specification.

The specification in Column [3] includes the natural log of retail revenues as a control variable. While including retail revenues as a control variable may help to control for the size of the utilities, revenues are directly related to the amount of energy efficiency activity that a utility performs. With an energy efficiency program, the quantity of electricity supplied by a utility is reduced. Regulators will adjust the rate of return utilities are allowed to gain. However, there are no expectations that revenues will be higher or lower.

Looking at some of the other variables in Table 3.7, the coefficient on the “Private” variable is positive and statistically significant at the 1 percent level in all specifications. The magnitude is large and roughly 3.5. This indicates that all other things equal, private utilities do a larger amount of energy efficiency compared to non-private utilities. This is consistent with the hypothesis about regulatory pressure. Once private utilities face less regulatory pressure, they will decrease their electricity reductions. The coefficient on the interaction term Priv*Dereg is also positive and statistically significant, but the magnitude is smaller than that of the coefficient on the "Private" variable. Depending on the specification, the coefficient varies from 1.576 to 1.946. The coefficient on Priv*Dereg implies that private utilities in states that deregulate their electricity market had more energy efficiency activity than other states prior to deregulation.

3.6.3 Robustness Checks

Following the main analysis, there are some interesting checks that can be performed to test the sensitivity of the main results. The first robustness check uses all 22 years of data from 1990 through 2011 and defines different post-periods based on when each state deregulated its electricity markets. For states that deregulated their electricity markets, the time period is divided into a pre-period before deregulation occurred and a post-period following deregulation. For states without electric restructuring activity, 2001 is used as the dividing year since this is roughly the midpoint of when deregulation occurred.[32]

The definition of the "Postperiod" variable has changed to reflect the additional deregulation timing details using all 22 years of data. To define the "Postperiod" variable in equation [19], for utilities that are located in states that deregulated, the variable is set to 1 if the year follows deregulation, and 0 otherwise. For utilities that are located in states that did not have any deregulation activity during the years analyzed, the "Postperiod" variable is a dummy

[32] The analysis was repeated using 1998 (the earliest year of deregulation activity) and 2002 (the latest year of deregulation activity) as the dividing point and the results do not change. Those results are available upon request.

variable that equals 1 if the year is greater than or equal to 2001 and 0 if the year is less than 2001.

The results when using all 22 years of data and specific state deregulation information for defining the "Postperiod" variable are presented in Table 3.8 and 3.9. Table 3.8 displays the results when using the energy efficiency levels in MWh as the dependent variable, while Table 3.9 contains the results when the natural log of energy efficiency is used as the dependent variable. In both tables, Column [1] shows the coefficients from the preferred specification of the main results, which includes all the interaction terms and a control variable for peak summer demand. Column [2] displays the results when all years of data and more specific state deregulation information are used in the regression. The results in Tables 3.8 and 3.9 are very similar to the main results in both magnitude and statistical significance. For private utilities, following state electricity market deregulation, there is a decrease in energy efficiency activity of approximately 200,000 MWh. The coefficient on the variable of interest is -179,157 MWh and is statistically significant at the 10 percent level. In the specification with the natural log of energy efficiency as the dependent variable, the coefficient is equal to -2.565 and is statistically significant at the 1 percent level. Using all 22 years of data and more detailed information about when each state deregulated supports the hypothesis that private firms decrease the amount of energy efficiency performed after their electricity markets are deregulated.

The second set of robustness checks that were performed are related to the states that started, but then suspended their electricity market deregulation activity. There are seven states that suspended their market restructuring activities and they are listed in Table 3.10. Two of these seven states – California and Arizona, started electricity deregulation and then suspended their activities. Column [3] of Table 3.10 lists the year when deregulation began, if applicable, and Column [4] shows the year when restructuring activity was suspended.

In the main regression specifications, utilities that are in states that suspended their deregulation activities are not considered as deregulated utilities. They are considered part of the comparison group with the utilities that are located in states with regulated electricity markets and their value for the "Dereg" variable is equal to 0. As a robustness check, California and Arizona are included in the deregulated states category because their electricity markets began implementing deregulation before suspending restructuring activity. Therefore, utilities that are in those states are given a value of 1 for their "Dereg" variable. The results when California and Arizona are included as deregulated states are listed in Column [2] of Table 3.11 for the levels and Column [2] of Table 3.12 for the natural logs. For comparison purposes, the results for the preferred specification are included in Column [1] of Tables 3.11 and 3.12. After including the two states into the deregulated states category, the results are consistent with the main results. The coefficients are negative and statistically significant. However, the magnitudes of the coefficients have decreased slightly.

Another check using the states with suspended deregulation activity involves dropping all the suspended states from the dataset. The results when those states are dropped from the dataset are presented in Column [3] of Tables 3.11 and 3.12, displaying levels and natural logs results, respectively. For the levels, the coefficient on the interaction term of interest is negative, but it is no longer statistically significant. However, the result for the natural logs is consistent with previous results. It is negative and statistically significant at the 1 percent level with a magnitude of -2.327.

3.7 Conclusion and Policy Implications

During the late 1990s, electricity market deregulation changed the structure of the electricity markets in the United States. The driving force behind this change was to encourage competition among electricity providers and many advocates pushed for deregulation in hopes of lower energy prices. This paper examines the impact of state electricity market deregulation on electric utilities' energy efficiency program usage. Using the change in deregulation and its differential impact on private and non-private utilities, I run a triple differences analysis and find that energy efficiency program activity declines for private utilities after a change in market structure. Following electricity market deregulation, energy efficiency activity decreases by 201,455 MWh to 232,435 MWh, depending on the regression specification, and the results are statistically significant. This result is consistent with the hypothesis that utilities reduce their energy efficiency activity when they are not as heavily regulated. Without pressure from their regulators, private utilities will no longer maintain the same level of energy efficiency.

Due to climate change concerns and the push for energy conservation during the last couple of decades, energy efficiency programs are becoming an important part of the United States' overall energy plan. If the goal of the government and state regulators is to encourage the usage of energy efficiency programs, the results in this paper indicate that they should pass regulations or legislation to urge utilities to do energy efficiency. If there is another push for electricity deregulation among states, this could have an impact on their energy efficiency activity.

Additionally, with the EPA's proposed Clean Power Plan, energy efficiency will become an increasingly important part of states' energy portfolio in the coming years as states work to reduce their carbon emission levels. As it becomes a priority for states to adopt and use energy efficiency programs, states that deregulated their electricity markets, may need to create new incentives for using energy efficiency programs. This could lead to the creation of tradable credits for energy efficiency and perhaps a new class of utilities to manage energy efficiency programs. One avenue for future research is analyzing the potential impact of the Clean Power Plan on energy efficiency levels. Another area of research is determining the cost of energy efficiency programs. Based on the results in this paper, once deregulation occurs, utilities will decrease their energy efficiency activity when they can. This implies that the programs are expensive to run. In order to encourage utilities to adopt and run these programs, it is important to understand exactly how expensive they are and whether there is a change in firm profitability once the programs are adopted. With the inclusion of more energy efficiency programs, there are additional areas for research to determine which programs are effective in reaching the end goal of energy conservation.

4. The Impact of Chinese Enterprise Restructuring on Employment, Wage Bills, and Productivity

4.1 Introduction

In recent decades, China has put into place many economic reforms as it moves towards a market economy. One important change is the transition of firm ownership structure from state-owned to private. Transitions of this nature began in the 1990s and continue today. When implementing changes in firm ownership on a large scale, the government needs to consider the trade-off between firm efficiency and welfare of society as a whole. Prior to reform of property rights, many state-owned enterprises (SOEs) suffered from inefficiencies, soft budget constraints, and low labor productivity. The government began restructuring thousands of firms from state-owned to private in the mid-1990s in an effort to reform inefficient firms.

From the welfare perspective, in addition to wages, SOEs can provide housing, health care benefits, and food subsidies for their workers (Cai, Park, and Zhao, 2008). State-owned enterprises also play an important role in the economy as a social safety net. As China lacked social insurance programs, such as unemployment insurance, state-owned firms often kept workers employed despite the redundancies in labor. Following the introduction of social benefit programs, the government also instituted aggressive layoffs in order to eliminate excess labor at other state-owned firms.

This paper analyzes the impact of the transfer of Chinese state-owned enterprises to private ownership on employment, wage bills, and labor productivity. The time period examined follows the implementation of many of these reforms (1998 through 2006), and firms' performance prior to privatization and after change in ownership structure are investigated.

Using a rich panel dataset, firms that transition are compared to those that remain state-owned within the same industry.

Previous empirical work has shown that privatization improves firm efficiency and profitability (Megginson and Netter, 2001). Improved firm performance is found for several different countries and time periods. The economic models of privatization support the idea that the increase in productivity and decrease in costs lead to decreases in employment and wages (Brown, et al., 2009). Using data on international airlines during 1973 through 1983, Ehrlich, et al. (1994) finds that completely changing from state to private ownership can increase the long-run annual rate of productivity growth by 1.6 to 2 percent and decrease the rate of unit cost by 1.7 to 1.9 percent. La Porta and López-de-Silanes (1999) analyzes the performance of 218 Mexican state-owned firms that privatized, comparing performance with industry-matched firms that existed before divestment. The study shows that output of privatized firms increased by 54.3 percent, sales per worker roughly doubled, and employment decreased by half. However, for the workers that remained employed, wages increased.

A major methodological hurdle when analyzing the impact of firm privatization is selection bias. Firms that are chosen for privatization may already be more productive and profitable than those chosen to remain state-owned. The concern is that positive performance ascribed to privatization could be due to the characteristics of the SOEs chosen for privatization rather than because of a change in property rights. Previous empirical research has tackled this problem using various methodological approaches, including firm fixed effects, the Heckman two-stage estimation method, and difference-in-differences matching.

Brown, Earle and Telegdy (2010) examine the impact of privatization on employment and wage effects in Hungary, Romania, Russia, and Ukraine following the dissolution of the

Soviet Union. To address selection bias in the privatization process, they employ a variety of different strategies including OLS, firm fixed effects, difference-in-differences matching, and random trend models. Using longitudinal methods and universal panel data on 30,000 initially state-owned manufacturing firms, Brown, et al. finds little evidence of job losses or wage cuts from either domestic or foreign privatization. For domestic privatization, estimates are close to zero for employment and negative (but small in magnitude) for wages. On the other hand, foreign privatization effects are almost always positive and sometimes large for both employment and wages. The findings are inconsistent with the simple trade-off in privatization between efficiency and worker welfare that has been assumed by many observers.

Hanousek, Kočenda, and Svejnar (2007) investigate the relationship between different ownership types on firm performance in the Czech Republic following privatization. A methodology using first differences combined with instrumental variables is used to address selection bias. The analysis uses a panel dataset, which includes the majority of medium and large firms that privatized, looks at the time period from 1996 through 1999, and finds that overall, the performance of privately-owned firms does not differ from that of state-owned firms. However, the results imply that concentrated foreign owners show stronger growth in sales and profits and concentrated domestic owners decrease employment.

In another study related to firm privatization in China, Bai, Lu, and Tao (2009) uses firm fixed effects and a Heckman two-stage estimation method to control for selection bias when examining the impact of privatization on social welfare and firm performance indicators. The results indicate that privatization had little impact on changes in employment, but increased sales, labor productivity, and firm profitability.

This analysis seeks to improve upon the existing privatization literature and provide further evidence on the impact of firm restructuring in China. To address the selection bias problem, a propensity score matching difference-in-differences estimation technique is employed. The propensity score matching technique uses observable characteristics to pair a firm that remains state-owned with one that transitions to private. Then, the difference-in-differences estimation controls for unobservable time invariant differences between the two groups.

The results indicate that firms that transition from state-owned to private decrease their employment on average by approximately 7 percent and reduce total real wages by 7 to 10 percent on-average. The estimates for labor productivity (measured as sales per worker) show increases of 11 to 26 percent on-average following a change in ownership structure. The employment and wage effects fade over time, while the productivity effects persist for a longer period of time. These estimates are consistent with previous theoretical work and empirical estimates. Theoretical models predict that employment would fall as a result of firms becoming more efficient, while labor productivity would rise. However, the effect on wages is theoretically ambiguous (Brown, Earle, Telegdy, 2010).

The remainder of the paper is laid out as follows: Section 4.2 provides background on the reforms related to Chinese SOEs during the past few decades. Section 4.3 describes the theory related to privatization and looks at how changes in ownership would impact employment, wages, and labor productivity. Section 4.4 discusses the methodology and potential selection bias involved in the privatization process. Section 4.5 describes the data, Section 4.6 provides and discusses the results, and Section 4.7 concludes and discusses next steps.

4.2 Background

After the establishment of the People's Republic of China in 1949, the development of heavy industry was emphasized. All input and output prices were set by government planners and the profitability of state enterprises was guaranteed. There were wage reforms in 1956 and SOEs were reformed in 1978 due to inefficiencies and low labor productivity (Cai, Park, and Zhao, 2008). Additional modifications to SOEs were made in the 1980s, as planned prices were slowly phased out and replaced by market prices, and changes were made allowing the enterprises to retain a larger share of their profits

After Deng Xiaoping's tour of the South in 1992 and the economic boom that followed, labor demand – driven mostly by newly developed private firms – increased in many cities (Cai, Park, and Zhao, 2008). However, by the early 1990s, SOEs continued to suffer great losses and in 1994, the government started privatizing small and medium SOEs while protecting larger enterprises – a policy they referred to as "seizing the large and letting go of the small" (Cao, Qian, and Weingast, 1999). This policy led to the privatization of all but the largest 300 state-owned firms (Megginson and Netter, 2001). In 1997, the 15th Congress of the Chinese Communist Party formally sanctioned ownership reforms of SOEs and legalized the development of private enterprises (Zhu, 2012). Also in that year, the government started aggressive SOE restructuring and established social benefit programs to help with the layoffs. During this time, tens of millions of workers were laid off. By the mid-2000s, labor became increasingly mobile and enterprises were allowed to give more weight to market conditions in making decisions about employment and wages (Cai, Park, and Zhao, 2008). Even though the number of state-owned enterprises has significantly decreased, they continue to make up an important portion of China's economy. In 2007, SOEs accounted for 35 percent of China's GDP.

Due to the gradual and continuing transition of SOEs to privately-owned firms, and the importance of SOEs in China's economy, the time period from 1998 through 2006 is used in this analysis. This is the time period following the implementation of government policies and reforms. Additionally, this is the time period used in previous literature, such as Bai, Lu, and Tao (2009) and Hsieh and Song (2015). Since this analysis uses the same time period, the estimates can be compared to those from previous studies.

4.3 Theoretical Predictions

State-owned enterprises are subject to different constraints than private firms. In China, this is particularly evident when examining employment in SOEs. Prior to the mid-1990s, open unemployment was non-existent in China (Cai, Park, and Zhao, 2008). The government protected workers and placed new graduates in state-sector jobs even when they were not needed. Firms were held to tight restrictions prohibiting them from firing more than 1 percent of their employees each year, they could not dismiss certain types of workers, and if they fired workers, they were expected to help them find new jobs. Workers were employed, but they were placed in firms that suffered from excess labor and inefficiency.

In contrast, private firms are motivated by profit maximization and firm efficiency and do not have the same restrictions with employment. They have more freedom to dismiss unproductive workers and can set wages at a competitive market level. As a result, one would expect that with a change in ownership status from state-owned to private, firms that transition would make cuts to their labor force and employment would decrease in those firms. If there is an excess of labor in those firms, the new management would lay off workers that are not necessary, thus decreasing their costs.

The expected sign on total wages following privatization is more ambiguous. If wages in the state-owned firms are too high because the firms are subsidizing their employees for housing and food, then wages would be expected to fall after the firms are privatized. However, wages could increase following privatization if the firms want to attract new workers or incentivize and reward existing workers using higher wages. By examining total wages, change in the wages for the firm as a whole can be examined, rather than wage per worker. Additionally, the total labor cost to the firm of restructuring can be analyzed from a monetary perspective.

Labor productivity (measured simply as the ratio between sales and employment) would be expected to rise after firms transition from state-owned to private. If firms are getting rid of inefficient employees, one would anticipate the firms to become more productive once those employees are let go. Using the methodology detailed below, these theoretical predictions will be tested to determine whether empirical analysis supports them.

4.4 Methodology

This paper examines the impact of Chinese firm privatization on three labor market outcomes: firm employment, total wage bills, and labor productivity, for firms that continue operating in the economy. The variable for labor productivity is calculated as the firm's real sales divided by the firm's total number of workers. For each of these outcome variables, the change in the value for a firm that transitions from state-owned to private is compared to a firm that remains state-owned during the entire time period. Additionally, these comparisons are done using firms that are in the same industry.

One concern when examining the effects of privatization is that firms that are privatized are those that are the most productive and profitable. They may be selected for privatization, while those that remain state-owned are more inefficient. Without a proper social insurance safety net in place, the government may want to maintain ownership of firms with worse prospects to prevent layoffs and wage cuts. Selection bias has been addressed in the literature using different methodologies. For example, Bai, Lu, and Tao (2009) tackle the problem by using firm fixed effects and a Heckman two-stage estimation method.

The main difference in this analysis compared to the existing literature is in the methodology. A propensity score matching difference-in-differences estimation technique is employed to address the possibility of selection bias. This technique first generates a propensity score for each firm using observable characteristics and matches a firm that remains state-owned with one that transitions from state-owned to private. After that, the difference-in-differences estimation controls for time invariant differences between the two groups.

Another issue with previous empirical privatization studies is the lack of time series data and small sample sizes. For example, La Porta and López-de-Silanes (1999) only have post-privatization information for a single year. With the panel dataset that is used in my analysis, transitions that take place over a longer period of time can be examined, and the impacts of privatization can be followed for a few years after the transition has occurred. This allows for determining whether the effects of firm restructuring are short-term or if they persist for a longer period of time. Additionally, the dataset that is used an industrial census of firms in China, which gives me a large sample of firms to work with. Details of this dataset are provided below in the data section.

In this analysis, two groups of firms are used: those that ever transition from SOEs to private firms and those that always remain state-owned. For the purpose of this analysis, the treatment group consists of firms that transition and those that remain state-owned are the comparison group. The firms are classified by registration type and whether or not a firm transitions based on whether or not their registration type changes. For the purpose of this paper, based on the definitions in the dataset, state-owned enterprises (SOEs) are defined as firms that are either: (i) Majority-owned by the central government or local government; (ii) Registered to the state but jointly operated with a non-state entity; or (iii) Wholly state-owned. Private firms are defined as those registered to natural persons, solely, in partnership, as limited liability enterprises or shareholding firms.

To generate propensity scores for the first stage of my analysis, the probability of a state-owned firm being privatized is predicted using a Probit model. The dependent variable is equal to 1 if the firm transitioned from state-owned to private and equal to 0 if it remained state-owned. The explanatory variables are chosen because they affect the decision to transition, and are also guided by the existing literature. In the Probit model, only the years of data prior to the privatization are used for firms that transition and all years of data for firms that remain state-owned are included.

Once these predicted values have been generated, they are used to match firms that transitioned (the treatment firms) to firms that remained state-owned (the comparison firms) in the same two-digit industry and year block. Each year block consists of four years; the year blocks are 1999-2002 and 2003-2006. The firms in the comparison group are present in the dataset during all years from 1998 through 2006. Matching is done with replacement, based on nearest neighbor and a common support condition is implemented using the minima and maxima comparison.

After each treatment firm is matched to a comparison firm, a difference-in-differences estimator is used to determine the impact of privatization on employment, total real wages, and productivity (measured as real sales divided by employment). This controls for unobservable time invariant differences between the two groups. The difference-in-differences matching (DDM) estimator is calculated as:

$$[20] \qquad \frac{1}{n}\sum_{n \in Trans}[(Y_t^{Trans} - Y_{t-1}^{Trans}) - (Y_t^{SOE} - Y_{t-1}^{SOE})]$$

For this analysis, the variables represented by *Y* include employment, total real wages, and productivity (sales per worker). The time period *t* is the year the firm transitions from state-owned to private, and the year *t-1* is one year prior to the firm transitioning. The estimators using the difference between *t+1* (one year after the transition) and *t-1*, and between *t+2* (two years after the transition) and *t-1* are also calculated to determine whether or not the impacts of restructuring persist over time.

4.5 Data

The data used in this paper come from the Annual Surveys of Industrial Production conducted by the Chinese government's National Bureau of Statistics (NBS) and consists of an unbalanced panel of firms from 1998 through 2006. The dataset includes all state-owned enterprises and all non-state owned firms whose annual sales revenue exceed five million RMB from its main business. It contains information on the firm and its operations including firm identification codes, ownership type, location information, data on employment and wages, sales, export value, value added and industry identifiers. The dataset provides information in nominal values and the data are adjusted to real values using the output deflators in Brandt, et al. (2009).[33]

As mentioned earlier, this study is only interested in firms that transitioned from state-owned to private enterprises (the treatment group) and those that remain state-owned (the comparison group). Additionally, only manufacturing firms and firms that continue to exist in the economy are included in the analysis. Following Jefferson, Rawski, and Zhang (2008), firms with fewer than eight employees are excluded because smaller firms may not have reliable accounting systems and may report unusually low or high values for certain variables. Table 4.1 contains summary statistics for the firms in the sample, separated by treatment and comparison groups. It shows that firms in the comparison group on-average employ more workers, pay more total wages, and have lower productivity than firms in the treatment group.

Additionally, the dataset that is used has matched firms on characteristics other than their identification code listed in the dataset. Using a list of legal entity codes or firm identification codes provided by Dr. Loren Brandt, firms that may have changed their legal entity codes over time are able to be matched. They are matched on other characteristics, such as firm location and industry. This helps identify firms that were mergers or acquisitions and allows the dataset to include firms in the panel even after the change in their legal entity code.

4.6 Does Firm Restructuring Matter?

4.6.1 Probit Model Results

Using the methodology described above in Section 4.4, first the probability of privatization is determined using a Probit model.[34] The variables included in the Probit model

[33] Information on the deflators can be found at: http://www.econ.kuleuven.be/public/N07057/CHINA/appendix/.

are similar to those used by Bai, et al (2009), with the addition of some variables. The model includes lagged log sales, lagged log sales squared, lagged sales per worker, lagged sales per worker squared, lagged current liability-asset ratio, lagged current liability-asset ratio squared, lagged non-SOE region share, lagged non-SOE three-digit industry share, the change in the non-SOE region share and the change in the non-SOE three-digit industry share. Additionally, the model includes fixed effects for year, three-digit industry, and region.[35] These variables are included to control for any shocks that occur that are specifically related to each year, industry, or region.

Table 4.2 displays the results of the Probit model. The results from the Probit model suggest that medium-sized firms are more likely to be privatized. The coefficients on the lagged natural log of sales and the lagged natural log of sales squared show an inverted U-shape to privatization. This is further supported by the variables for lagged sales per worker, lagged sales per worker squared, lagged current liability-asset ratio, and lagged current liability-asset ratio squared. The coefficient on the variable lagged non-SOE share in a three-digit industry is positive and statistically significant, suggesting that firms are more likely to privatize if a higher share of other firms in the same three-digit industry have already transitioned to private firms.

4.6.2 Difference-in-Differences Results

4.6.2.1 Baseline Results

Once the propensity scores are generated using the Probit model described above, then each treatment firm is matched to a comparison firm and the impact of privatization is estimated

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[34] This model was also run using a logit model and yielded similar results in terms of sign and significance. They are available upon request.

[35] The regions are based on the following groupings of provinces: (1) Coastal – Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang; (2) Inland – Anhui, Henan, Hubei, Hunan, Jiangxi, Shanxi; (3) Northeast – Heilongjiang, Jilin, Liaoning; (4) Southwest – Chongqing, Guangxi, Guizhou, Sichuan, Yunnan; (5) Northwest – Gansu, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Tibet, Xinjiang.

using a difference-in-differences matching (DDM) estimator. The difference between the treatment and comparison groups is taken before and after privatization occurred using the process described earlier in the methodology section. The results for employment, wage bills, and productivity (as measured by sales per worker) are presented in log form in Table 4.3. For each variable, the results are displayed for the year of transition, one year after the transition, and two years after the transition. The first column identifies the year of analysis, the second column displays the observed mean, the third column shows the bootstrapped standard errors using 500 repetitions, the fourth column presents the Z-statistic, and the fifth column lists the number of matched pairs for that year. The stars next to the means show the level of statistical significance. One star represents the 10 percent significance level, two stars corresponds to the 5 percent significance level, and three stars denotes the 1 percent significance level.

For employment, the results are negative and statistically significant at the 1 percent level in the year of transition and one year after the transition. However, the effect is strongest in the year of transition where the DDM estimator is equal to -0.076. Having taken into consideration the initial differences between the two groups of firms, firms that are privatized have 7.6 percent lower employment relative to those firms that remain state-owned. This result makes intuitive sense if there was a redundancy in labor at state-owned firms prior to privatization. Following the firm restructuring, owners would layoff unneeded employees to cut costs. One year after the transition, employment is still lower by 6.7 percent and the result is statistically significant. However, two years after the transition, the sign on the coefficient is still negative and of a smaller magnitude than the previous years, but it is no longer statistically significant. A few years after the transition, the firms may have already made adjustments to their labor force and are no longer cutting employment as much as they were immediately following the transition to becoming privately owned. These results are in line with what the theory predicts and match the findings of other empirical analyses.

For total real wages, the results are always negative and statistically significant. The differentials range from -6.3 percent to -10.4 percent. Again, this makes intuitive sense because if employees were overpaid prior to restructuring, their wages would be cut following the transition to a private firm. For wages, there is not a clear pattern in the changes over time. The differential decreases from the year of transition to one year after the transition, but then it increases from one year after the transition to two years following the transition. While the sign on wages is theoretically ambiguous, the results here support a story where workers were paid too much when the firms were state-owned and the firms cut wages after they become privately owned.

Meanwhile, productivity, as measured by sales per worker, increased every year following privatization. The results for productivity are significant in all years, and range from 11 percent to 26 percent. The differential increases from the year of transition to one year after the transition, and then it falls from one year after the transition to two years after privatization. Following the transition from being a state-owned firm to a private firm, it is expected that productivity will increase as firms are eliminating excess labor and pushing to make the firms more efficient, and the results support this hypothesis.

Based on the results presented in Table 4.3, the effects of restructuring appear to be strongest in the year of transition and fade over time for employment. The impact on total real wages is significant in all years, but the strength of the significance varies from year to year. However, the impact on productivity seems to remain for at least two years after the transition. The longer term impacts of privatization can be examined with additional years of data.

4.6.2.2 Results based on State Affiliations

As a check on the baseline results and to further examine the impacts of privatization on employment, total wages, and productivity, the sample is split based on the state affiliations of firms prior to privatization, when they are all state-owned. Using the same matched sample from the main analysis, the firms that transition are separated into two groups: (1) those that are affiliated with the Central or Provincial governments, and (2) those that are not affiliated with the Central or Provincial governments. The firms are divided in this way to determine whether there is a difference in how they respond to restructuring based on their state affiliations prior to privatization. The Chinese government is highly decentralized and restructuring was implemented differently for firms based on their level of affiliation. This analysis seeks to determine whether there is a difference in the way enterprises affiliated with the Central or Provincial governments responded to restructuring. After the firms are split into these two groups, the difference-in-differences analysis is rerun. The results are presented in Tables 4.4a and 4.4b. Table 4.4a presents the results for firms that are affiliated with the Central or Provincial governments, while Table 4.4b includes the results for firms that are not affiliated with the Central or Provincial governments.

For firms affiliated with the Central or Provincial governments, the impact of privatization on employment is negative, but only statistically significant in the year of transition. The results show that in the year of transition, firms that are privatized have 15 percent lower employment relative to the firms that remain state-owned. The results for total real wages are more ambiguous. The impact on total real wages is negative in the year of transition and slightly positive one year after the transition, but neither of these results are statistically significant. The impact on productivity is significant in both years, with firms that transition having 34 percent and 46 percent higher productivity relative to the control firms in the year of transition and one year after the transition, respectively. Again these results are in line with the theoretical predictions; firms that become privately owned will cut their labor forces and productivity will increase.

Looking at the results for firms that were not affiliated with the Central or Provincial governments, the impacts of privatization are statistically significant for employment, total real wages, and productivity in both the year of the transition and one year after the transition. The employment differentials range from -6.1 percent to -6.9 percent, the total real wage differentials are approximately -6.9 percent for both years, and the productivity differentials range from 9 percent to 24 percent. These values are all smaller in magnitude compared to the results for firms that are affiliated with the Central or Provincial governments, although the signs are all what one would expect based on theoretical predictions. Overall, the results are consistent with those for the full sample, which were presented in the previous section.

In another variation of splitting the sample based on affiliation prior to transitioning, the sample is split into two different groups: (1) those that are affiliated with the Central, Provincial, or City and Prefecture governments, and (2) those that are not affiliated with the Central, Provincial, or City and Prefecture governments. The sample is split in this way to determine whether there is a difference based on a firm's affiliation. In this version of the analysis, firms affiliated with City or Prefecture governments are included with those affiliated with the Central or Provincial governments. Again, after the sample is split, the difference-in-differences analysis is rerun. The results for the firms that are affiliated with the Central, Provincial, or City and Prefecture governments are presented in Table 4.5a. Table 4.5b presents the results for those firms that are not affiliated with the Central, Provincial, or City and Prefecture governments.

For firms that are affiliated with the Central, Provincial, or City and Prefecture governments prior to transitioning, the impacts on employment, total real wages, and productivity are all statistically significant. The results for employment and total real wages are significant at the 1 percent level and are similar in the year of transition and one year after the transition. The employment differential is -15 percent in both years, and the total real wage differential is -17 percent the year of transition and -16 percent one year after transitioning. For productivity, the differentials are 13 percent and 31 percent, the year of transition and one year after transitioning, respectively.

The results for firms that are not affiliated with the Central, Provincial, or City and Prefecture governments prior to transitioning are statistically significant at the 5 percent level for employment the year of transition, and significant at the 1 percent level for productivity in both years. The impact of privatization on employment is negative in both years. However, the result is only significant in the year of transition. Firms that transition have 4.8 percent lower employment relative to the firms that remain state-owned in that year. The impact on total real wages is negative in both years, but neither of these results are statistically significant. The productivity differentials range from 9.9 to 24 percent, and are statistically significant at the 1 percent level. These results are all consistent with the hypothesis of firms eliminating excess labor and cutting wages to decrease costs and increase productivity following a change in ownership from state-owned to private.

4.7 Conclusions and Next Steps

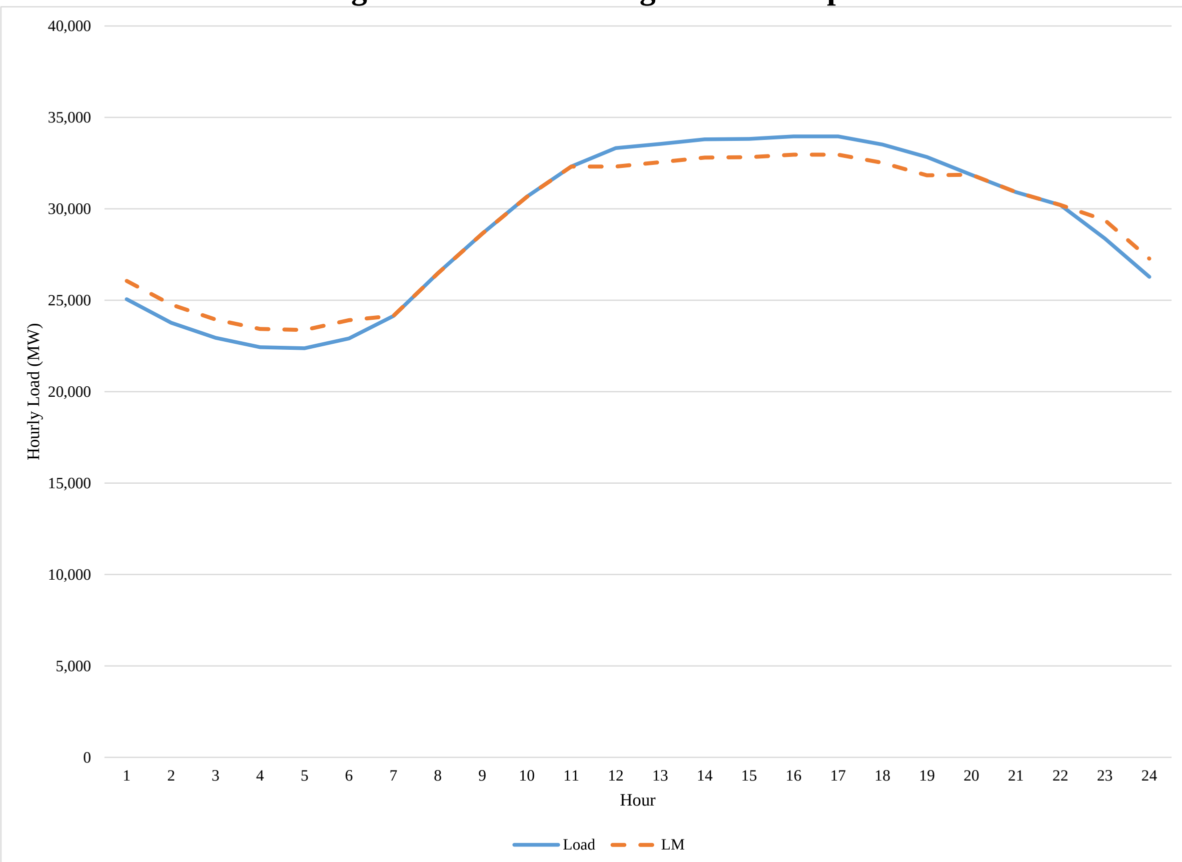
In an attempt to improve inefficient state-owned enterprises, the Chinese government introduced reforms that privatized state-owned enterprises. It is important to understand the impact of privatization on the social welfare and labor market outcomes in China. Using a propensity score matching differences-in-differences estimation technique, the impact of enterprise restructuring on labor market outcomes in China is determined by looking at firms that transition during the time period from 1998 through 2006. Enterprise restructuring is defined as firms that transition from state-owned to privately-owned, and changes in employment, total real wages, and productivity as measured by sales per worker are examined. After using a Probit model to match the firms, the differences between firms that transition and those that remain state-owned are investigated for the year of transition, one year after transitioning and two years after the transition.

The results suggest that prior to restructuring, firms were indeed inefficient and overstaffed. Following privatization, firms that transitioned decreased their employment on-average by approximately 7 percent and reduced total real wages by 7 percent to 10 percent on-average. At the same time, productivity rose on-average 11 percent to 26 percent following enterprise restructuring. The effects for employment and wages fade over time, while the productivity effects last longer. The results generally hold if the firms are split into different groups based on their state affiliations prior to privatization. The employment and wage effects are negative, while the productivity effects are positive. These effects are consistent with the story of firm restructuring following a change from being a state-owned enterprise to becoming a private firm, with firms shedding excess employment, cutting wages, and increasing productivity. The results are also in line with the theoretical predictions and other empirical analyses in the privatization literature. After implementing these changes to make the firms more efficient and increase sales, firms may decide to hire additional workers or increase the wages of existing workers to reward them for their efforts. However, an analysis of this sort would most likely require additional years of data.

The analysis in this paper leads to many interesting follow-up questions and avenues of further research. Other variables, such as profits and access to credit, could be examined to determine if they were also affected by firm privatization. The restructuring of state-owned firms also leads to changes in homeownership, child care, and other services previously provided by SOEs. The privatization of state-owned firms could lead to decreases in other benefits previously provided by SOEs that cannot be measured by only looking at the change in wages over time. Additional research could look at whether these services are provided by the government or if workers need to rely on private provision following firm privatization. Another question that arises from this research is whether or not restructuring induces entry or exit in certain regions or industries. The focus of this paper is on firms that continue to exist in the Chinese economy. While it is difficult to measure entry and exit in the current dataset, this is an important question to answer since growth or decline of firms in certain regions or industries could have many public welfare implications.

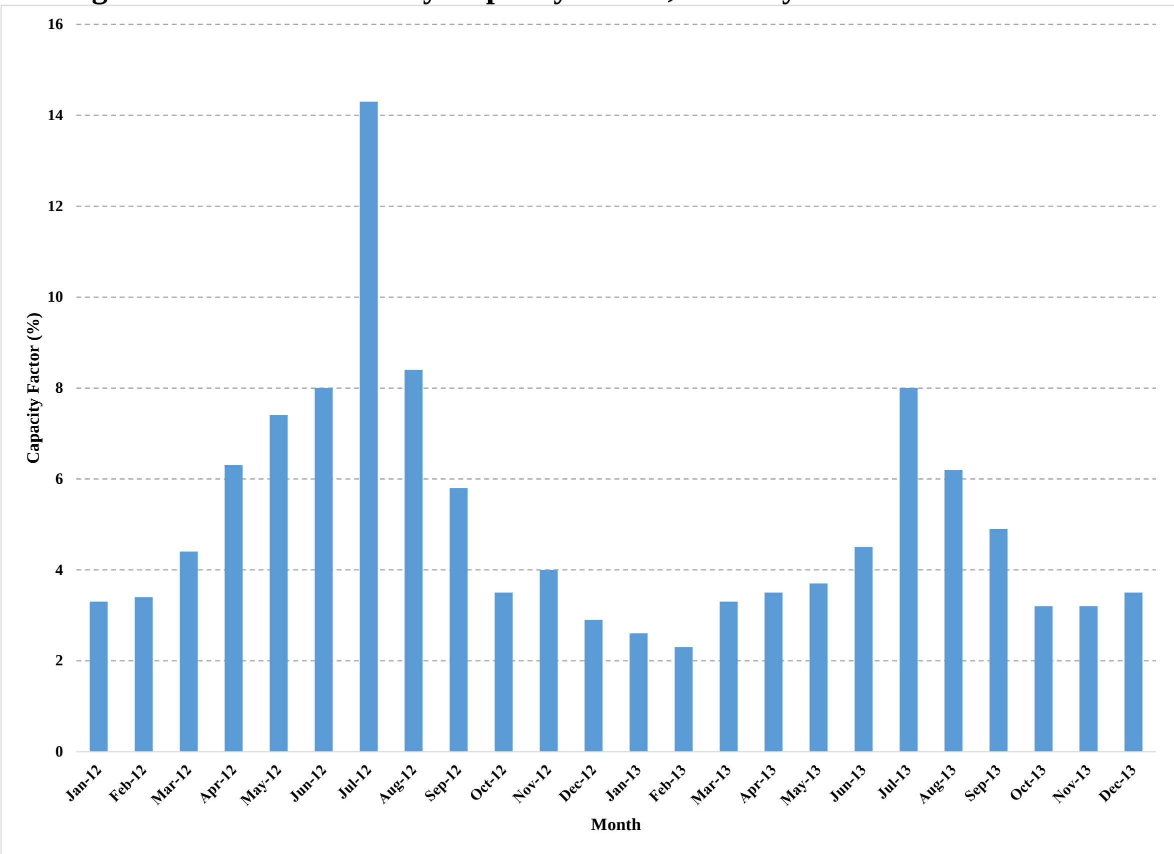
Figures and Tables

Figure 2.1: Load Management Example



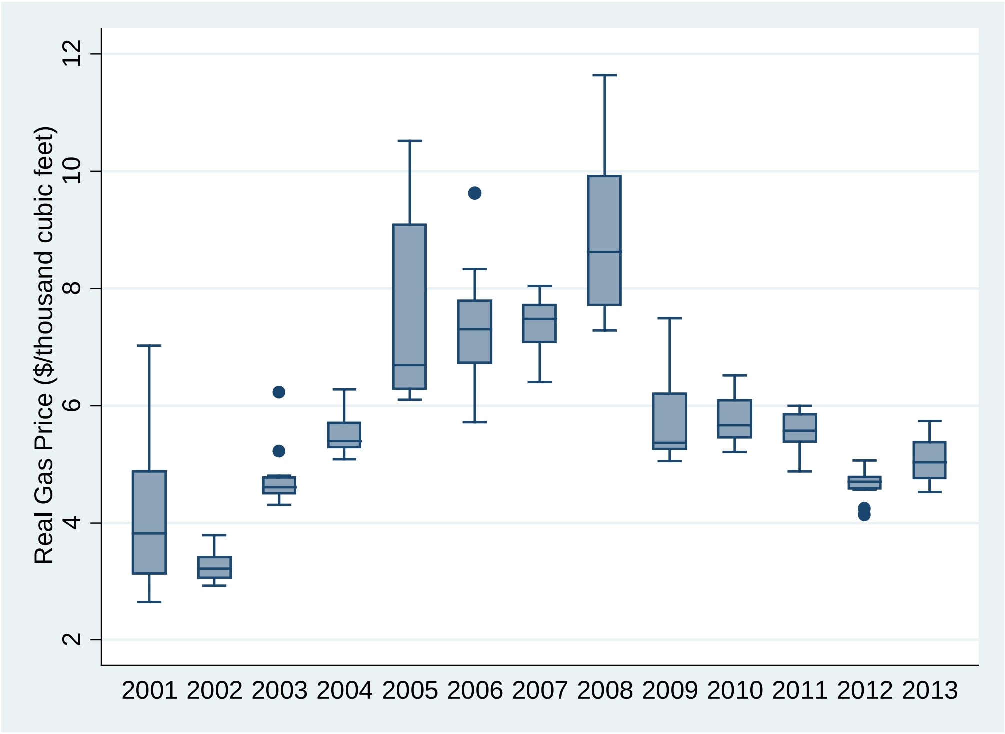
Source: NYISO load data from July 19, 2013.
Notes: LM line represents a hypothetical 1,000 MW LM program during peak hours.

Figure 2.2: NGCT Monthly Capacity Factor, January 2012 – December 2013



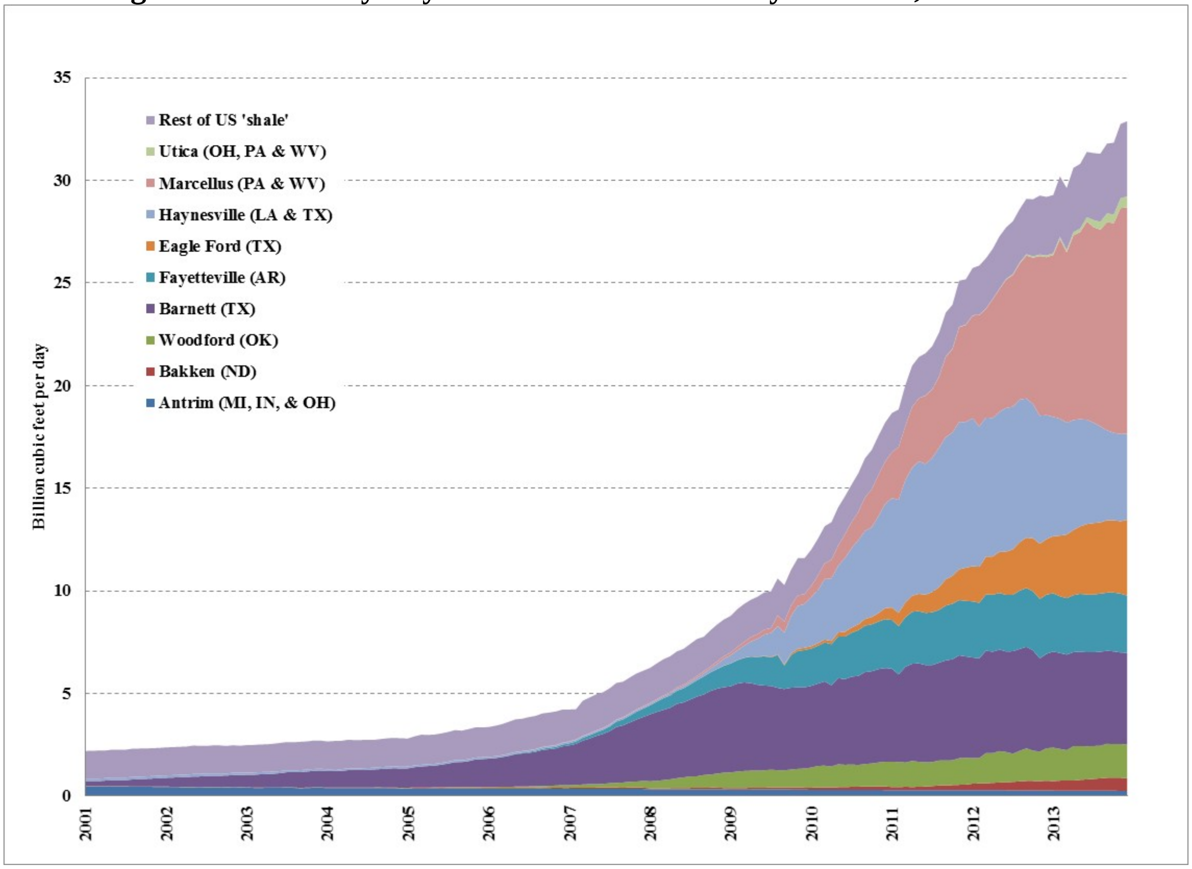
Source: Data are from EIA.

Figure 2.3: U.S. Natural Gas Citygate Prices, 2001 – 2013



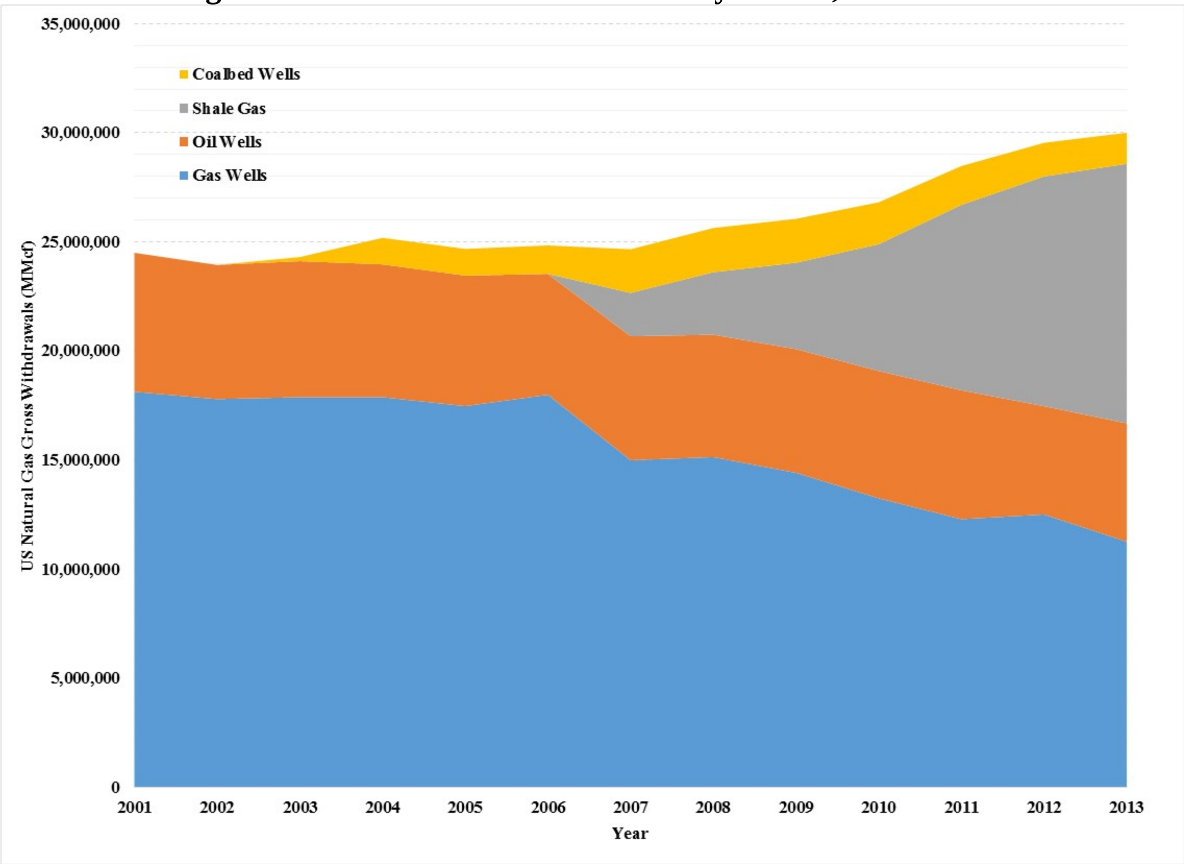
Source: Data are from EIA.
Notes: Prices are in real 2013 dollars.

Figure 2.4: Monthly Dry Shale Gas Production by Location, 2001 – 2013



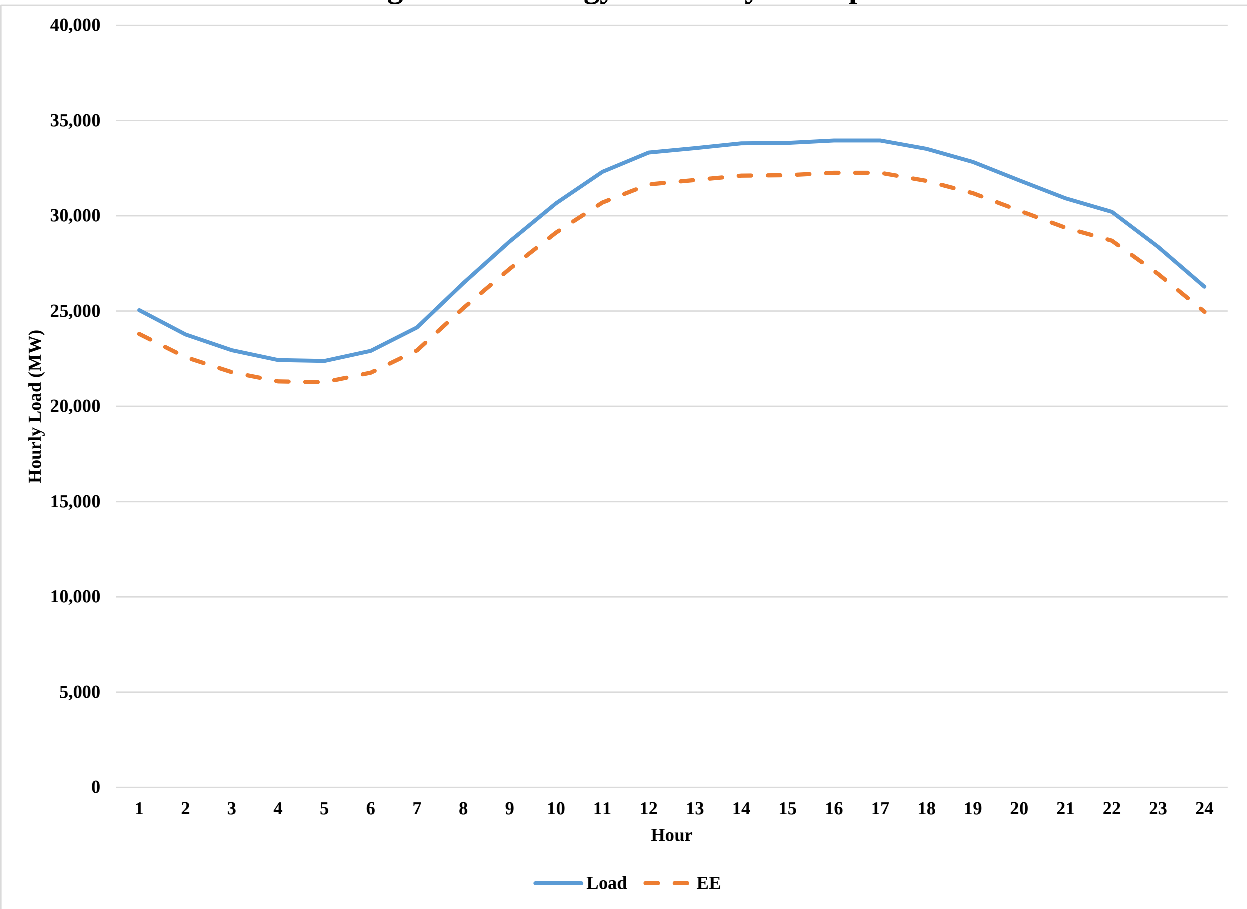
Source: Data are from EIA.

Figure 2.5: Natural Gas Withdrawals by Source, 2001 – 2013



Source: Data are from EIA.

Figure 3.1: Energy Efficiency Example



Source and Notes: Load data are from the New York Independent System Operator.
The dashed orange line represents a hypothetical energy efficiency program that reduces energy usage by 5 percent of actual demand.

Figure 3.2: Energy Efficiency Activity over Time, Non-Private Utilities

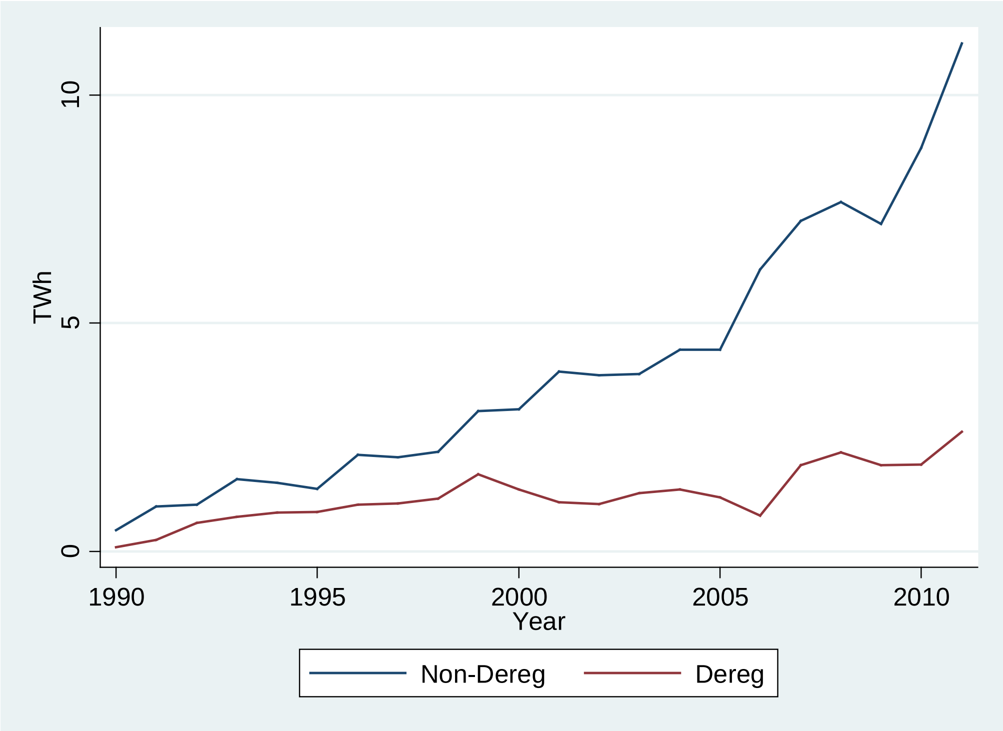


Figure 3.3: Energy Efficiency Activity over Time, Private Utilities

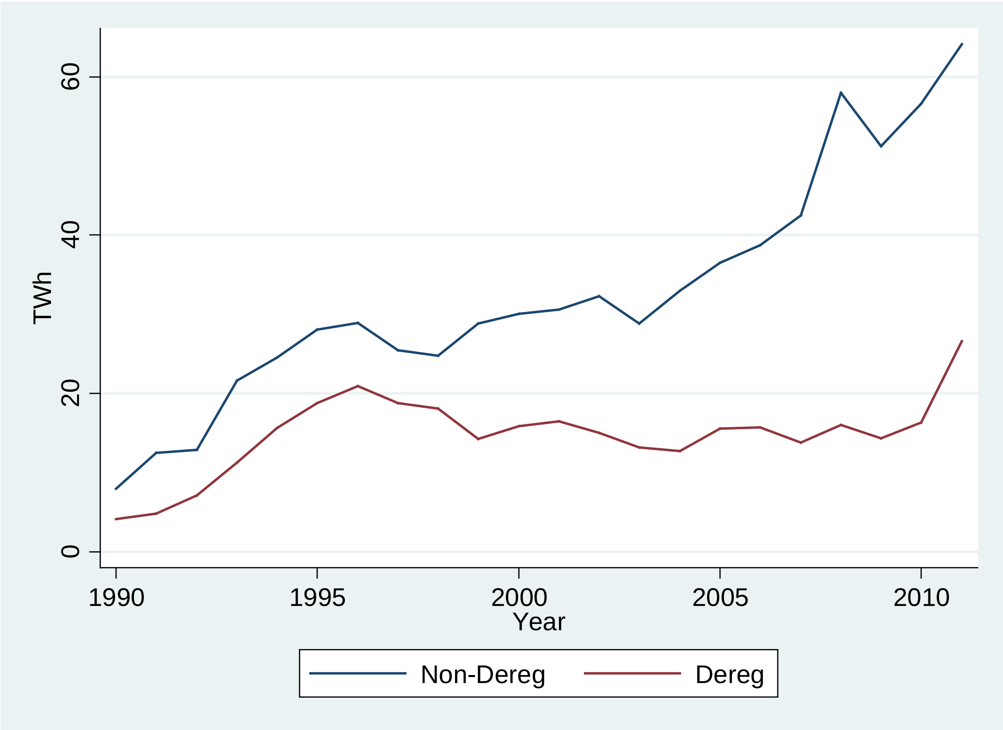


Table 2.1: Annual Load Management Program Totals

Year	LM Potential Peak Reductions (MW)	LM Actual Peak Reductions (MW)	Potential Peak Reductions / Peak Summer Demand	Actual Peak Reductions / Peak Summer Demand
2001	27,272	11,548	0.0546	0.0231
2002	26,460	9,193	0.0472	0.0164
2003	24,899	9,015	0.0432	0.0156
2004	20,636	9,035	0.0349	0.0153
2005	20,963	10,188	0.0406	0.0198
2006	21,021	11,062	0.0243	0.0128
2007	22,937	12,421	0.0361	0.0195
2008	24,518	11,840	0.0392	0.0190
2009	25,558	11,791	0.0431	0.0199
2010	25,302	12,438	0.0392	0.0192
2011	25,734	11,874	0.0373	0.0172

Source: EIA 861 Form 3

Table 2.2: Summary Statistics, Full Sample

Variable Name	Mean	Std. Dev.	Min	Max
Peak Summer Demand (MW)	708	2,346	0	26,750
Retail Revenues ($000s)	217,185	798,839	0	11,235,765
Cooperative	0.37	0	0	1
Local Government	0.49	0	0	1
Private	0.14	0	0	1
LM Actual / Peak Summer Demand	0.02	0.09	0	3
LM Potential / Peak Summer Demand	0.04	0.13	0	3
LM Actual Reductions (MW)	13	79	0	1,726
LM Potential Reductions (MW)	28	159	0	5,370

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
The combined sample has 9,574 observations.

Table 2.3a: Summary Statistics by Group in Pre-Period, Non-Private Utilities

Variable Name	Gen Ever = 0 Comparison Group Mean	Gen Ever = 0 Comparison Group Std. Dev.	Gen Ever = 1 Treatment Group Mean	Gen Ever = 1 Treatment Group Std. Dev.
Peak Summer Demand (MW)	80	272	335	757
Retail Revenues ($000s)	21,376	38,799	66,919	194,602
LM Actual / Peak Summer Demand	0.022	0.08	0.014	0.05
LM Potential / Peak Summer Demand	0.034	0.12	0.024	0.07
LM Actual Reductions (MW)	2	9	8	45
LM Potential Reductions (MW)	4	17	16	71

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
There are 4,572 observations in the comparison group and 1,968 in the treatment group.

Table 2.3b: Summary Statistics by Group in Pre-Period, Private Utilities

Variable Name	Gen Ever = 0 Comparison Group Mean	Gen Ever = 0 Comparison Group Std. Dev.	Gen Ever = 1 Treatment Group Mean	Gen Ever = 1 Treatment Group Std. Dev.
Peak Summer Demand (MW)	3,035	5,238	4,410	4,986
Retail Revenues ($000s)	940,529	1,428,997	1,308,719	1,711,640
LM Actual / Peak Summer Demand	0.004	0.01	0.014	0.04
LM Potential / Peak Summer Demand	0.010	0.02	0.033	0.07
LM Actual Reductions (MW)	23	84	70	206
LM Potential Reductions (MW)	87	266	161	446

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
There are 203 observations in the comparison group and 745 in the treatment group.

Table 2.4a: LM Program Usage Regression Results, Non-Private Utilities

VARIABLES	(1) LM Act Ann / Hist Pk Sum Load	(2) LM Act Ann / Hist Pk Sum Load	(3) LM Act Ann / Hist Pk Sum Load
Gen Ever*Post	-0.0169***	-0.0195***	-0.0151***
	(0.00498)	(0.00516)	(0.00511)
Gen Ever	-0.00731*	-0.00899**	-0.00465
	(0.00383)	(0.00372)	(0.00381)
Postperiod	0.0264***	0.0258***	0.0229***
	(0.00427)	(0.00431)	(0.00436)
Real Retail Revenue		1.25e-08*	9.32e-09
		(7.21e-09)	(6.84e-09)
Constant	0.0216***	0.0206***	0.0158
	(0.00266)	(0.00262)	(0.0147)
State Dummies	No	No	Yes
Observations	8,089	7,786	7,786
R-squared	0.016	0.017	0.103

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: LHS variable is LM Actual Annual Effects normalized by Historical Peak Summer Load. Historical peak load is the peak summer load for 2001 or first year of data available for each utility.
Data are for the time period 2001 – 2011.
Utilities with observations only in 2006 are dropped from the sample.
Non-private utilities include cooperative and local government utilities.

Table 2.4b: LM Program Capacity Regression Results, Non-Private Utilities

VARIABLES	(1) LM Pot Ann / Hist Pk Sum Load	(2) LM Pot Ann / Hist Pk Sum Load	(3) LM Pot Ann / Hist Pk Sum Load
Gen Ever*Post	-0.0481***	-0.0518***	-0.0449***
	(0.00905)	(0.00930)	(0.00922)
Gen Ever	-0.00933*	-0.0142***	-0.00742
	(0.00539)	(0.00517)	(0.00550)
Postperiod	0.0601***	0.0596***	0.0543***
	(0.00848)	(0.00859)	(0.00846)
Real Retail Revenue		2.69e-08**	2.50e-08**
		(1.26e-08)	(1.16e-08)
Constant	0.0336***	0.0324***	0.0231
	(0.00375)	(0.00372)	(0.0240)
State Dummies	No	No	Yes
Observations	8,089	7,786	7,786
R-squared	0.026	0.029	0.102

Standard errors clustered by utility in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: LHS variable is LM Potential Annual Effects normalized by Historical Peak Summer Load.
Historical peak load is the peak summer load for 2001 or first year of data available for each utility.
Data are for the time period 2001 – 2011.
Utilities with observations only in 2006 are dropped from the sample.
Non-private utilities include cooperative and local government utilities.

Table 2.5a: LM Program Usage Regression Results, Private Utilities

VARIABLES	(1) LM Act Ann / Hist Pk Sum Load	(2) LM Act Ann / Hist Pk Sum Load	(3) LM Act Ann / Hist Pk Sum Load	(4) LM Act Ann / Hist Pk Sum Load
Gen Ever*Post	0.0192	0.0197	0.0191	0.0165
	(0.0137)	(0.0145)	(0.0149)	(0.0142)
Gen Ever	0.0107***	0.0106***	0.00627*	0.00418
	(0.00326)	(0.00341)	(0.00364)	(0.00582)
Postperiod	-0.000447	-0.000678	1.66e-05	0.000796
	(0.00189)	(0.00198)	(0.00226)	(0.00279)
Real Retail Revenue		1.67e-09	1.94e-09	2.02e-09
		(1.65e-09)	(1.66e-09)	(1.84e-09)
Deregulation Flag			-0.0107	
			(0.00972)	
Constant	0.00372***	0.00222	0.0113	-0.0246**
	(0.00127)	(0.00201)	(0.00890)	(0.0106)
State Dummies	No	No	No	Yes
Observations	1,213	1,165	1,165	1,165
R-squared	0.009	0.010	0.012	0.118

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: LHS variable is LM Actual Annual Effects normalized by Historical Peak Summer Load.
Historical peak load is the peak summer load for 2001 or first year of data available for each utility.
Data are for the time period 2001 – 2011.
Utilities with observations only in 2006 are dropped from the sample.
Private utilities include investor-owned utilities and retail power marketers.

Table 2.5b: LM Program Capacity Regression Results, Private Utilities

VARIABLES	(1) LM Pot Ann / Hist Pk Sum Load	(2) LM Pot Ann / Hist Pk Sum Load	(3) LM Pot Ann / Hist Pk Sum Load	(4) LM Pot Ann / Hist Pk Sum Load
Gen Ever*Post	0.0177	0.0177	0.0163	0.0126
	(0.0139)	(0.0147)	(0.0152)	(0.0142)
Gen Ever	0.0231***	0.0226***	0.0132*	0.0130*
	(0.00685)	(0.00681)	(0.00692)	(0.00749)
Postperiod	0.00103	0.000545	0.00205	0.00310
	(0.00222)	(0.00210)	(0.00297)	(0.00354)
Real Retail Revenue		3.90e-09	4.49e-09**	3.17e-09*
		(2.37e-09)	(2.20e-09)	(1.85e-09)
Deregulation Flag			-0.0232*	
			(0.0123)	
Constant	0.0102**	0.00675*	0.0265**	-0.0336***
	(0.00391)	(0.00363)	(0.0122)	(0.0117)
State Dummies	No	No	No	Yes
Observations	1,213	1,165	1,165	1,165
R-squared	0.012	0.016	0.025	0.236

Standard errors clustered by utility in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: LHS variable is LM Potential Annual Effects normalized by Historical Peak Summer Load.
Historical peak load is the peak summer load for 2001 or first year of data available for each utility.
Data are for the time period 2001 – 2011.
Utilities with observations only in 2006 are dropped from the sample.
Private utilities include investor-owned utilities and retail power marketers.

Table 3.1: States with Deregulated Electricity Markets

State	State Abbreviation	Year of Deregulation
Massachusetts	MA	1998
New York	NY	1998
Rhode Island	RI	1998
Connecticut	CT	2000
Illinois	IL	2000
Maine	ME	2000
New Jersey	NJ	2000
Pennsylvania	PA	2000
Delaware	DE	2001
District of Columbia	DC	2001
Maryland	MD	2001
New Hampshire	NH	2001
Ohio	OH	2001
Michigan	MI	2002
Oregon	OR	2002
Texas	TX	2002

Sources:
Energy Information Administration

Table 3.2: Annual Energy Efficiency Totals

Year	Energy Efficiency Annual Totals (MWh)
1990	17,060,936
1991	23,432,348
1992	25,565,174
1993	40,203,068
1994	49,720,120
1995	55,332,076
1996	59,857,108
1997	55,467,136
1998	48,775,616
1999	49,691,724
2000	52,826,648
2001	52,946,056
2002	53,228,424
2003	48,253,568
2004	52,662,988
2005	59,000,096
2006	63,075,684
2007	67,277,888
2008	86,010,464
2009	76,911,768
2010	87,094,816
2011	120,658,706

Source: EIA 861 Form 3

Table 3.3: Summary Statistics, Full Sample

Variable Name	Mean	Std. Dev.	Min	Max
Energy Efficiency Annual Total (MWh)	16,930	246,748	0	14,917,724
Peak Summer Demand (MW)	247	1,287	0	29,628
Retail Revenues ($000s)	61,200	373,425	0	11,235,765
Cooperative	0.29	0.46	0	1
Local Government	0.64	0	0	1
Private	0.06	0	0	1

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
The combined sample has 62,194 observations.

Table 3.4: Summary Statistics by Ownership Type in Pre-Period

Variable Name	Non-Private		Private	
	Mean	Std. Dev.	Mean	Std. Dev.
Energy Efficiency Annual Total (MWh)	910	15,962	195,082	625,025
Peak Summer Demand (MW)	64	245	2,625	3,914
Retail Revenues ($000s)	9,780	37,969	590,359	947,113

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
There are 28,754 observations for non-private utilities and 1,855 for private utilities.

Table 3.5a: Summary Statistics, Non-Private Utilities in Pre-Period

Variable Name	No Deregulation (Comparison Group)		Deregulation (Treatment Group)	
	Mean	Std. Dev.	Mean	Std. Dev.
Energy Efficiency Annual Total (MWh)	750	13,500	1,529	23,123
Peak Summer Demand (MW)	65	256	57	200
Retail Revenues ($000s)	9,880	39,330	9,395	32,167

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
There are 22,842 observations in the comparison group and 5,912 in the treatment group.

Table 3.5b: Summary Statistics, Private Utilities in Pre-Period

Variable Name	No Deregulation (Comparison Group)		Deregulation (Treatment Group)	
	Mean	Std. Dev.	Mean	Std. Dev.
Energy Efficiency Annual Total (MWh)	211,694	730,701	168,837	404,474
Peak Summer Demand (MW)	2,391	3,871	2,995	3,955
Retail Revenues ($000s)	505,834	931,677	724,388	956,536

Source: EIA 861 Forms 1 and 3
Notes: Retail Revenues are in real 2013 dollars.
Some variables are not reported for certain utilities.
There are 1,136 observations in the comparison group and 719 in the treatment group.

Table 3.6: Triple Difference Results – Levels

VARIABLES	(1) Energy Efficiency Annual Total	(2) Energy Efficiency Annual Total
Priv*Dereg*Postperiod	-232,435**	-201,455*
	(115,420)	(106,320)
Priv*Dereg	-41,130	-104,018
	(66,483)	(68,282)
Priv*Postperiod	252,369**	184,424**
	(109,468)	(84,331)
Dereg*Postperiod	559.3	932.1
	(861.0)	(964.9)
Private	191,703***	-56,682
	(57,697)	(65,267)
Dereg	547.2	1,536
	(744.7)	(1,052)
Postperiod	992.2***	-2,667**
	(352.9)	(1,338)
Peak Demand Summer		111.6***
		(37.93)
Constant	642.7***	-6,145***
	(201.5)	(2,342)
Observations	50,904	50,352
R-squared	0.072	0.299

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
LHS variable is Energy Efficiency Total Annual Effects in MWh.
Data are for the time period 1990 – 2011, excluding 1998 – 2001.
Only utilities in all 18 years of the dataset are included in the sample.

Table 3.7: Triple Difference Results – Natural Logs

VARIABLES	(1) ln Energy Efficiency	(2) ln Energy Efficiency	(3) ln Energy Efficiency
Priv*Dereg*Postperiod	-2.117***	-2.369***	-2.685***
	(0.627)	(0.651)	(0.697)
Priv*Dereg	1.877**	1.576**	1.946***
	(0.788)	(0.667)	(0.682)
Priv*Postperiod	0.156	0.519	0.398
	(0.345)	(0.357)	(0.368)
Dereg*Postperiod	-0.0981**	-0.0965*	-0.0844*
	(0.0499)	(0.0512)	(0.0502)
Private	4.660***	3.392***	3.590***
	(0.513)	(0.430)	(0.449)
Dereg	0.0346	-0.00763	-0.0272
	(0.0695)	(0.0652)	(0.0652)
Postperiod	0.0984***	-0.0895***	-0.165***
	(0.0243)	(0.0255)	(0.0277)
ln Peak Demand Summer		0.444***	0.273***
		(0.0279)	(0.0375)
ln Retail Revenues			0.178***
			(0.0277)
Constant	0.334***	-0.821***	-1.753***
	(0.0293)	(0.0624)	(0.165)
Observations	50,904	50,352	49,081
R-squared	0.230	0.326	0.353

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
LHS variable is ln (Energy Efficiency Total Annual Effects + 1).
Data are for the time period 1990 – 2011, excluding 1998 – 2001.
Only utilities in all 18 years of the dataset are included in the sample.
Control variables are ln (Peak Demand Summer + 1) and ln (Real Retail Revenues + 1).

Table 3.8: Triple Difference Results – Levels, Baseline vs. All Years

VARIABLES	(1) Baseline	(2) All Years
Priv*Dereg*Postperiod	-201,455*	-179,157*
	(106,320)	(93,459)
Priv*Dereg	-104,018	-110,557
	(68,282)	(72,504)
Priv*Postperiod	184,424**	168,927**
	(84,331)	(78,171)
Dereg*Postperiod	932.1	943.9
	(964.9)	(747.3)
Private	-56,682	-43,132
	(65,267)	(58,812)
Dereg	1,536	1,667
	(1,052)	(1,177)
Postperiod	-2,667**	-2,142**
	(1,338)	(1,068)
Peak Demand Summer	111.6***	109.3***
	(37.93)	(35.72)
Constant	-6,145***	-6,384***
	(2,342)	(2,375)
Observations	50,352	61,465
R-squared	0.299	0.308

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
LHS variable is Energy Efficiency Total Annual Effects in MWh.
Column [1] presents baseline result equivalent to Column [2] in Table 6.
Column [2] displays results when all 22 years of data from 1990 – 2011 are used in regression.

Table 3.9: Triple Difference Results – Natural Logs, Baseline vs. All Years

VARIABLES	(1) Baseline	(2) All Years
Priv*Dereg*Postperiod	-2.369***	-2.565***
	(0.651)	(0.606)
Priv*Dereg	1.576**	1.528**
	(0.667)	(0.689)
Priv*Postperiod	0.519	0.401
	(0.357)	(0.335)
Dereg*Postperiod	-0.0965*	-0.0336
	(0.0512)	(0.0461)
Private	3.392***	3.749***
	(0.430)	(0.440)
Dereg	-0.00763	-0.0433
	(0.0652)	(0.0694)
Postperiod	-0.0895***	-0.0306
	(0.0255)	(0.0225)
ln Peak Demand Summer	0.444***	0.391***
	(0.0279)	(0.0260)
Constant	-0.821***	-0.682***
	(0.0624)	(0.0570)
Observations	50,352	59,336
R-squared	0.326	0.324

Standard errors clustered by utility in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes:
LHS variable is ln (Energy Efficiency Total Annual Effects + 1).
Column [1] presents baseline result equivalent to Column [2] in Table 7.
Column [2] displays results when all 22 years of data from 1990 – 2011 are used in regression.
The control variable is ln (Peak Demand Summer + 1).

Table 3.10: States with Suspended Electricity Market Deregulation

State	State Abbreviation	Year of Deregulation	Year of Suspension
California	CA	1998	2002
Arizona	AZ	2001	2005
Nevada	NV	N/A	2002
Montana	MT	N/A	2003
New Mexico	NM	N/A	2003
Arkansas	AR	N/A	2003
Virginia	VA	N/A	2007

Sources:
Energy Information Administration

Table 3.11: Triple Difference Results – Levels, Suspended States Robustness Checks

VARIABLES	(1) Baseline	(2) CA and AZ in Deregulated Group	(3) Dropping Suspended States
Priv*Dereg*Postperiod	-201,455*	-170,663*	-95,246
	(106,320)	(93,836)	(73,987)
Priv*Dereg	-104,018	-132,471*	-46,244
	(68,282)	(78,788)	(55,437)
Priv*Postperiod	184,424**	177,708**	100,578*
	(84,331)	(81,434)	(59,507)
Dereg*Postperiod	932.1	-29,628	810.6
	(964.9)	(19,594)	(867.9)
Private	-56,682	-51,278	28,101
	(65,267)	(62,540)	(31,375)
Dereg	1,536	32,777	866.3
	(1,052)	(20,334)	(753.0)
Postperiod	-2,667**	3,966	-1,021
	(1,338)	(3,420)	(701.8)
Peak Demand Summer	111.6***	111.3***	60.50***
	(37.93)	(37.61)	(18.66)
Constant	-6,145***	-13,433**	-2,819***
	(2,342)	(6,626)	(1,073)
Observations	50,352	50,352	47,219
R-squared	0.299	0.300	0.255

Standard errors clustered by utility in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
LHS variable is Energy Efficiency Total Annual Effects in MWh.
Data are for the time period 1990 – 2011, excluding 1998 – 2001.
Only utilities in all 18 years of the dataset are included in the sample.
Column [1] presents baseline result equivalent to Column [2] in Table 6.
Column [2] displays results when California and Arizona are included in listed of deregulated states.
Column [3] shows results when states with “Suspended” deregulation activity are dropped from the dataset.

Table 3.12: Triple Difference Results – Natural Logs, Suspended States Robustness Checks

VARIABLES	(1) Baseline	(2) CA and AZ in Deregulated Group	(3) Dropping Suspended States
Priv*Dereg*Postperiod	-2.369***	-1.992***	-2.327***
	(0.651)	(0.660)	(0.685)
Priv*Dereg	1.576**	1.229*	1.926***
	(0.667)	(0.675)	(0.692)
Priv*Postperiod	0.519	0.435	0.481
	(0.357)	(0.359)	(0.413)
Dereg*Postperiod	-0.0965*	-0.468***	-0.0595
	(0.0512)	(0.118)	(0.0506)
Private	3.392***	3.461***	3.161***
	(0.430)	(0.430)	(0.456)
Dereg	-0.00763	0.372***	-0.00146
	(0.0652)	(0.112)	(0.0648)
Postperiod	-0.0895***	-0.00735	-0.112***
	(0.0255)	(0.0348)	(0.0251)
ln Peak Demand Summer	0.444***	0.440***	0.410***
	(0.0279)	(0.0277)	(0.0285)
Constant	-0.821***	-0.900***	-0.736***
	(0.0624)	(0.0676)	(0.0624)
Observations	50,352	50,352	47,219
R-squared	0.326	0.328	0.319

Standard errors clustered by utility in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes:
LHS variable is ln (Energy Efficiency Total Annual Effects + 1).
Data are for the time period 1990 – 2011, excluding 1998 – 2001.
Only utilities in all 18 years of the dataset are included in the sample.
Column [1] presents baseline result equivalent to Column [2] in Table 7.
Column [2] displays results when California and Arizona are included in listed of deregulated states.
Column [3] shows results when states with "Suspended" deregulation activity are dropped from the dataset.
The control variable is ln (Peak Demand Summer + 1).

Table 4.1: Summary Statistics

Variable	Mean	
	Treatment	**Control**
Employment (Number of Workers)	287	386
Total Real Wages (10,000 Yuan)	2,443	3,615
Real Sales (10,000,000 Yuan)	39	42
Sales per Worker (10,000,000 Yuan / Number of Workers)	0.16	0.14
Current Liability-Asset Ratio	1.77	1.65

Table 4.2: Probit Model Results

VARIABLES	(1) Probit Model – Transition Ever
Lagged ln sales	0.0454**
	(0.0198)
Lagged ln sales squared	-0.0404***
	(0.00357)
Lagged sales per worker	1.237***
	(0.129)
Lagged sales per worker squared	-0.232***
	(0.0372)
Lagged current liability-asset ratio	0.0178**
	(0.00742)
Lagged current liability-asset ratio squared	-0.000100
	(8.95e-05)
Lagged non-SOE region share	-0.510
	(0.707)
Lagged non-SOE 3-digit industry share	17.02***
	(3.155)
Non-SOE region delta	7.15e-06***
	(1.46e-06)
Non-SOE 3-digit industry delta	0.000108***
	(2.28e-05)
Constant	-0.670
	(0.527)
Dummies for year	Yes
Dummies for three-digit industry	Yes
Dummies for region	Yes
Pseudo R^2	0.1360
Observations	16,542

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3: Difference-in-Differences Baseline Results

ln(Employment)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0757***	0.0193	3.91	1,735
One Year after Transition	-0.0668***	0.0250	2.67	1,174
Two Years after Transition	-0.0261	0.0301	0.87	910

ln(Real Wages)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0715***	0.0246	2.91	1,717
One Year after Transition	-0.0633*	0.0332	1.91	1,161
Two Years after Transition	-0.1042**	0.0414	2.52	900

ln(Sales per Worker)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	0.1094***	0.0280	3.91	1,733
One Year after Transition	0.2577***	0.0348	7.40	1,173
Two Years after Transition	0.2159***	0.0406	5.32	909

Notes:

Observed mean calculated as: $\frac{1}{n}\sum_{n \in Trans}\left[\left(Y_t^{Trans} - Y_{t-1}^{Trans}\right) - \left(Y_t^{SOE} - Y_{t-1}^{SOE}\right)\right]$

Bootstrapped standard errors in parenthesis using 500 repetitions.
Statistical significance at the 10, 5, and 1 percent levels are represented by *, **, ***, respectively.

Table 4.4a: Difference-in-Differences Results, Starting Affiliation is Central or Provincial

ln(Employment)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.1512**	0.0717	2.11	137
One Year after Transition	-0.1353	0.1177	1.15	88

ln(Real Wages)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0994	0.0945	1.05	137
One Year after Transition	0.0045	0.1450	0.03	87

ln(Sales per Worker)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	0.3353***	0.0923	3.63	137
One Year after Transition	0.4618***	0.1346	3.43	88

Notes:

Observed mean calculated as: $\frac{1}{n}\sum_{n\in Trans}\left[(Y_t^{Trans} - Y_{t-1}^{Trans}) - \left(Y_t^{SOE} - Y_{t-1}^{SOE}\right)\right]$

Bootstrapped standard errors in parenthesis using 500 repetitions.
Statistical significance at the 10, 5, and 1 percent levels are represented by *, **, ***, respectively.

Table 4.4b: Difference-in-Differences Results, Starting Affiliation is neither Central nor Provincial

ln(Employment)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0693***	0.0191	3.63	1,598
One Year after Transition	-0.0612**	0.0249	2.46	1,086

ln(Real Wages)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0691***	0.0265	2.60	1,580
One Year after Transition	-0.0688**	0.0339	2.03	1,074

ln(Sales per Worker)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	0.0900***	0.0285	3.16	1,580
One Year after Transition	0.2411***	0.0354	6.81	1,085

Notes:

Observed mean calculated as: $\frac{1}{n}\sum_{n\in Trans}\left[(Y_t^{Trans} - Y_{t-1}^{Trans}) - \left(Y_t^{SOE} - Y_{t-1}^{SOE}\right)\right]$

Bootstrapped standard errors in parenthesis using 500 repetitions.
Statistical significance at the 10, 5, and 1 percent levels are represented by *, **, ***, respectively.

Table 4.5a: Difference-in-Differences Results, Starting Affiliation is Central, Provincial, or City and Prefecture

ln(Employment)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.1549***	0.0380	4.08	455
One Year after Transition	-0.1548***	0.0506	3.06	313

ln(Real Wages)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.1710***	0.0458	3.73	454
One Year after Transition	-0.1631***	0.0620	2.63	312

ln(Sales per Worker)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	0.1340**	0.0574	2.34	455
One Year after Transition	0.3111***	0.0616	5.05	313

Notes:

Observed mean calculated as: $\frac{1}{n}\sum_{n\in Trans}\left[(Y_t^{Trans} - Y_{t-1}^{Trans}) - \left(Y_t^{SOE} - Y_{t-1}^{SOE}\right)\right]$

Bootstrapped standard errors in parenthesis using 500 repetitions.
Statistical significance at the 10, 5, and 1 percent levels are represented by *, **, ***, respectively.

Table 4.5b: Difference-in-Differences Results, Starting Affiliation is neither Central, Provincial, nor City and Prefecture

ln(Employment)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0476**	0.0199	2.39	1,280
One Year after Transition	-0.0347	0.0296	1.17	861

ln(Real Wages)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	-0.0357	0.0281	1.27	1,263
One Year after Transition	-0.0266	0.0403	0.66	849

ln(Sales per Worker)

Year (t)	Observed Mean	Bootstrap Standard Error	Z-Statistic	Matched Pairs
Year of Transition	0.0986***	0.0313	3.14	1,278
One Year after Transition	0.2383***	0.0410	5.81	860

Notes:

Observed mean calculated as: $\frac{1}{n}\sum_{n\in Trans}\left[\left(Y_t^{Trans} - Y_{t-1}^{Trans}\right) - \left(Y_t^{SOE} - Y_{t-1}^{SOE}\right)\right]$

Bootstrapped standard errors in parenthesis using 500 repetitions.
Statistical significance at the 10, 5, and 1 percent levels are represented by *, **, ***, respectively.

Bibliography

861 Webfile Layout for 2010, downloaded with EIA 861 data from http://www.eia.gov/cneaf/electricity/page/eia861.html

A National Assessment of Demand Response Potential (2009), available at http://www.ferc.gov/legal/staff-reports/06-09-demand-response.pdf (National Assessment)

Alcott, H., and Greenstone, M. (2012) "Is There an Energy Efficiency Gap?", *The Journal of Economic Perspectives*, **26(**1), 3-28.

Arimura, T., Li, S., Newell, R., and Palmer, K. (2011) "Cost-Effectiveness of Electricity Energy Efficiency Programs", National Bureau of Economic Research (NBER) Working Paper No. 17556, Cambridge, MA.

Association for Demand Response & Smart Grid (ADS) (2010), "Demand Response & Smart Grid – State Legislative and Regulatory Policy Action Review: October 2008 – May 2010".

Association for Demand Response & Smart Grid (ADS) (2011), "Demand Response & Smart Grid – State Legislative and Regulatory Policy Action Review: May 2010 – June 2011".

Bai, C., Lu, J., Tao, Z. (2009), "How does Privatization work in China?", *Journal of Comparative Economics,* **37**(3), 453-470.

Brandt, L., Biesebroeck, J., Zhang, Y., (2009) "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing", National Bureau of Economic Research (NBER) Working Paper No. 15152, Cambridge, MA.

Brown, J., Earle, J., Telegdy, A. (2010), "Employment and Wage Effects of Privatisation: Evidence from Hungary, Romania, Russia and Ukraine", *The Economic Journal*, **120**(4), 683-708.

Brown, J., Earle, J., Vakhitov, V. (2006), "Wages, Layoffs, and Privatization: Evidence from Ukraine", *Journal of Comparative Economics*, **34**(2), 272-294.

Cai, F., Park, A., Zhao, Y. (2008), The Chinese Labor Market in the Reform Era. In L. Brandt & T. Rawski (Eds.), *China's Great Economic Transformation* (pp. 167-214). New York, NY: Cambridge University Press.

Cao, Y., Qian, Y., Weingast, B. (1999), "From Federalism, Chinese Style, to Privatization, Chinese Style", *Economics of Transition*, **7**(1), 103-131.

Ehrlich, I., Gallais-Hamonno, G., Liu, Z., Lutter R. (1994), "Productivity Growth and Firm Ownership: An Empirical Investigation", *Journal of Political Economy*, **102**, 1006-1038.

Faruqui, A., and Sergici, S. (2010), "Household Response to Dynamic Pricing of Electricity – A Survey of 15 Experiments", *Journal of Regulatory Economics*, **38(**2), 193-225.

The Federal Energy Regulatory Commission Staff, (2010), "National Action Plan on Demand Response", Docket No. AD09-10.

Hanousek, J., Kočenda, E., Svejnar, J. (2007), "Origin and Concentration: Corporate Ownership, Control and Performance in Firms after Privatization", *Economics of Transition*, **15**(1), 1-31.

Hsieh, C., and Song, Z. (2015), "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China", National Bureau of Economic Research (NBER) Working Paper No. 21006, Cambridge, MA.

Jaffe, A., and Stavins, R. (1994), "The energy-efficiency gap", *Energy Policy*, **22(**10), 804-810.

Jefferson, G., Rawski, T., Zhang, Y. (2008), "Productivity Growth and Convergence across China's Industrial Economy", *Journal of Chinese Economic and Business Studies*, **6**(2), 120-141.

Joskow, P. (2007), "Competitive Electricity Markets and Investment in New Generating Capacity", *The New Energy Paradigm* (Dieter Helm, editor), Oxford University Press.

Joskow, Paul L. and Richard Schmalensee, (1983), *Markets for Power*, Cambridge: Massachusetts Institute of Technology Press.

La Porta, R., and López-de-Silanes, F. (1999), "Benefits of Privatization – Evidence from Mexico", *Quarterly Journal of Economics*, **114**(4), 1193-1242.

Megginson, W., and Netter, J. (2001), "From State to Market: A Survey of Empirical Studies on Privatization", *Journal of Economic Literature*, **39**(2), 321-389.

Naughton, B. (2007), *The Chinese Economy: Transitions and Growth*, Cambridge: Massachusetts Institute of Technology Press.

Rosenbaum, P., and Rubin, D. (1985), "Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score", *The American Statistician*, **39**(1), 33-38.

Rosenbaum, P., and Rubin, D. (1983), "The Central Role of Propensity Score in Observational Studies for Causal Effects", *Biometrika*, **70**(1), 41-55.

"Status of Electricity Restructuring by State", information gathered and downloaded from http://www.eia.gov/electricity/policies/restructuring/restructure_elect.html

"Status of State Electric Industry Restructuring Activity", downloaded from http://large.stanford.edu/publications/coal/references/docs/restructure.pdf

U.S. Department of Energy, (2002), "A Primer on Electric Utilities, Deregulation, and Restructuring of U.S. Electricity Markets", Version 2.0.

U.S. Department of Energy, (2006), "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them: A Report to the United States Congress Pursuant to Section 1252 of the Energy Policy Act of 2005".

U.S. Energy Information Administration, (2011), "Electric Power Annual 2010", *Independent Statistics and Analysis*.

Zhu, X. (2012), "Understanding China's Growth: Past, Present, and Future", *Journal of Economic Perspectives*, **26**(4), 103-124.

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